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An agent-based model to simulate stakeholders' negotiation regarding land development in the Elbow River watershed in southern Alberta

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by

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by

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Abstract

The study of *coupled human and natural systems* known as CHANS research requires the incorporation of both biological and social aspects and neglecting one or the other can lead to their incomplete understanding. This study aims at incorporating stakeholders' perspectives and facilitating their negotiation over land development in the Elbow River watershed in southern Alberta considered as a CHANS. To achieve this objective, a scientific framework was developed which integrates concepts and techniques from three disciplines: Complexity theory, Post-normal science, and Artificial intelligence (AI). A negotiation support system was developed in a web-based environment that includes an agent-based model as the core component. Concepts of post-normal science were incorporated to guide the engagement of stakeholders. A fuzzy approach was considered to tackle the inherent uncertainties in the way stakeholders expressed their perspectives. Rather than attempting to find a unique, optimum solution regarding land development, an agreement was sought that was satisfactory at a minimum level to all stakeholders involved in the negotiation. To equip the agents representing the stakeholders with the intelligence required to conduct human-like behaviors such as communication and learning, AI techniques were employed to enable them to learn from previous rounds of negotiation. The proposed modeling system was tested using land development scenarios in the Elbow River watershed. The results reveal that the model acts as a virtual laboratory in which the stakeholders gain a better understanding of each other's perspectives, while investigating alternative scenarios of land development in order to reach an agreement. They also indicate how learning and considering the opponents'

perspectives can make their satisfaction values converge more quickly to an agreement point. The novelty of this study lies in the successful integration of the concepts and methods originating from three disciplines to capture the complexity of a CHANS. Moreover, this is one of the few studies that incorporate the spatial context in a negotiation to address issues related to land development. The negotiation support system developed in this study can be very useful for decision makers who wish to consider stakeholders' perspectives when dealing with multiple objectives in a spatial context.

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To Canada and its wonderful people who made my PhD studies a joyful experience.

Many thanks to my family in Iran, my sister and brothers: I could not ask for a better family.

And finally I have been blessed with the greatest parents in the world: Zahra and Ali; their unconditional love and endless support made this possible.

Dedication

To my mother

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List of Abbreviations

Symbol	Definition
ABM	Agent-based modeling
ACE	Agent-based computational economics
AI	Artificial intelligence
AHP	Analytic hierarchy process
CanSIS	Canadian Soil Information System
CHANS	Coupled human and natural systems
GIS	Geographic information system
HTTP	Hypertext Transfer Protocol
JDBC	Java Database Connectivity
JSP	JavaServer Pages
MCDA	Multi-criteria decision analysis
MD	Municipal District
MVC	Model/View/Controller
PCM	Pairwise comparison matrix
RL	Reinforcement Learning
SQL	Structured Query Language
XML	Extensible Markup Language

Introduction

Coupled human and natural systems (CHANS) research

Coupled human and natural systems (CHANS) are systems in which both human and natural elements interact (Liu *et al.*, 2007a) to shape patterns and dynamics (Turner *et al.*, 2007). Understanding the complexities of human-nature interactions in such systems is essential both to the human well-being and the sustainability of other species (Alberti *et al.*, 2011). Numerous approaches have been proposed to study these systems, namely systems ecology (Odum, 1983), political ecology (Zimmere and Bassett, 2003), and complexity theory (Levin, 1998). These approaches rely on the same fundamental concepts: comprehending the interactions of the constituent elements of the systems and investigating the properties of those interactions that bring about their complex behavior (Stevenson, 2011).

In recent years, the importance of developing an integrated scientific framework to study CHANS has been recognized by scientists (Liu *et al.*, 2007a). Such a framework known as the *CHANS research* aims at studying the complex interactions that connect human to natural sub-systems of ecosystems through the integration of knowledge from multiple disciplines (Alberti *et al.*, 2011). CHANS research builds upon disciplines such as ecology, geography, and sociology; it moves beyond them by focusing on an integrated framework. It encourages the incorporation of stakeholders (Alberti *et al.*, 2011) and emphasizes the notion that neglecting this element can yield an incomplete picture of the CHANS (Walsh and McGinnis, 2008). This is due to the fact that today hardly any environmental modelling effort can be presented without some kind of reference to stakeholders and their engagement (Voinov and Bousquet, 2010).

However building such an integrated framework is not an easy task (Baker, 2006). The main reason for such difficulty lies in the traditional separation of ecological and social sciences (Rosa and Dietz, 1998). For long, social scientists have solely focused on human interactions, considering the environmental influences to be constant while ecologists have concentrated on environmental aspects in which humans are considered external (Liu *et al.*, 2007a), therefore neglecting or underestimating their influence. Moreover, social scientists and researchers in natural sciences employed different scientific approaches (Lélé and Norgaard, 2005); even the notion of model varies across these disciplines (Alberti *et al.*, 2011). Another major challenge of CHANS research is the understanding of how large-scale phenomena emerge from the local interactions of multiple agents (Liu *et al.*, 2007a). A set of approaches and tools need to be developed for the study of CHANS to accommodate the complexity of human-nature interactions.

To tackle the mentioned challenges, this study proposes the integration of concepts and approaches from three disciplines: complexity theory, post-normal science, and artificial intelligence. Complexity theory provides the essential scientific rationale to study the complexities of CHANS. It is believed that Complexity theory is able to bridge the gap between ‘hard’ approaches in which optimum, quantitative solutions are sought to solve well-defined problems and ‘soft’ approaches which aim at tackling ill-defined problems that involve psychological, social, and cultural elements (Portugali, 2006). Post-normal science focuses on the management of uncertainties and plurality of perspectives through the engagement of stakeholders and introduces the concept of extended peer community (Petersen *et al.*, 2011). Artificial intelligence, which aims at building intelligent machines (Poole *et al.*, 1998), provides the techniques and tools to incorporate intelligence required for such an engagement. Figure 1.1 illustrates the framework used in this study to address the CHANS research challenges.

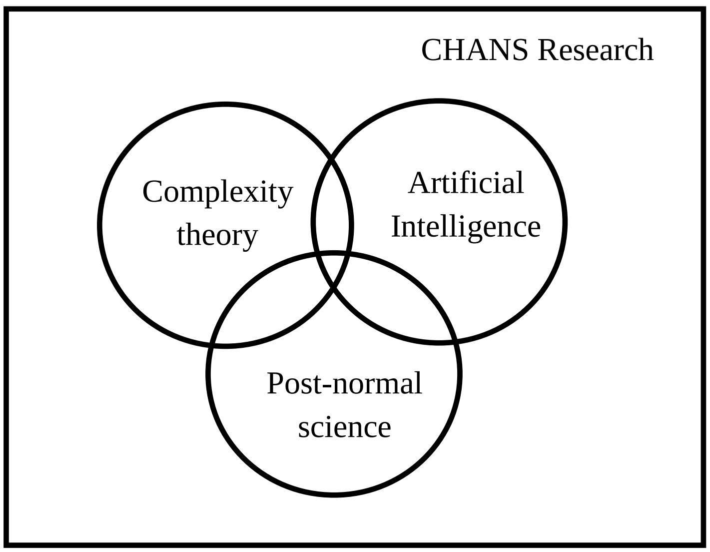


Figure 0.1. The conceptual framework of this research

Complexity theory and Post-normal science

Complexity theory is a discipline that aims at studying *complex systems* (Lewin, 1999). It attempts to understand how the global patterns and behaviors of a system emerge from the interactions of its constituent parts (Waldrop, 1992). It has been the scientific backbone of a large number of approaches that all gather under the general banner of complexity research (Manson, 2001). To comprehend the scope and objectives of complexity theory, first the characteristics of complex systems need to be described.

Complex systems are systems that demonstrate the following characteristics (Miller and Page, 2009; Folke, 2006):

- *Feedback*: A feedback mechanism means that the future state of the system is influenced by its current state. Feedback mechanism provides a loop in which the system responds to perturbation either in the same direction (positive feedback) or in the opposite direction (negative feedback).
- *Non-linearity*: In a non-linear system, an output is not proportional to its input, so a minor perturbation may cause a major effect (Drazin, 1992).
- *Emergence*: Emergence refers to the appearance of higher-level properties and behaviors of a system originating from the collective dynamics of that system's components that cannot be analyzed from the study of its constituent elements in isolation.
- *Adaptation*: In biological terms, adaptation means a change in the structure of an organism that helps it survive more efficiently in its environment. In the context of humans, adaptation can be interpreted as the learning ability. Humans and numerous other living creatures have the potential to learn from experiences and change their decisions based on these experiences.
- *Self-organization*: Self-organization can be defined as the spontaneous emergence of macroscopic non-equilibrium organized structures from the interaction of basic elements without the force of any external agent (Heylighen, 2003).

Complexity theory emerged as a response to the need for studying systems that exhibit complex systems characteristics. Several scientists came to the conclusion that the reductionist approach is not sufficient for understanding systems with higher amounts of complexity such as CHANS (Anderson, 1972; Jørgensen, 2002; Kauffman, 2007). This is due to the fact that the reductionist approach considers a system as nothing more than the sum of its constituent elements and attempts to study it by reducing it to its fundamental units, as practiced in classical mechanics or thermodynamics (Kauffman, 2007). However, in spite of the success of the reductionist approach in studying several natural and social systems, they are unable to tackle systems of high complexity. In his famous article, "More is Different", Nobel Laureate Philip Anderson argues that reductionism is wonderful but not enough (Anderson, 1972).

Due to the unpredictable interactions between the elements of complex systems, complexity theory proposes the notion that in these systems the whole is more than the sum of the parts (Waldrop, 1992) and global patterns emerge from simple local interactions among the elements of the system. Complexity theory has been applied in a wide range of areas, from psychology (Klinkman, 2007) to economy (Lorenz, 2009) and international relations (Axelrod, 1997) to coupled human and natural systems (Liu *et al.*, 2007b).

In CHANS, people and nature interact reciprocally and form complex feedback loops. Due to these interactions, such systems demonstrate the qualities of complex systems and therefore CHANS research can highly benefit from complexity theory approaches. The ecological and socioeconomic impacts of human-nature couplings may not be immediately observable or predictable because of time lags between the human-nature interactions and the appearance of ecological and socioeconomic consequences (Alberti, 2008). Complexity theory can aid CHANS research by handling characteristics such as reciprocal interactions, feedbacks and the emergence of patterns from local behaviors (Liu *et al*., 2007b).

The increasing acceptance of complexity theory which accounts for the unpredictability of non-linear systems has motivated the development of *Post-normal science* (Laugharne, 2002). Post-normal science has emerged as a new scientific practice to deal with situations where the legitimate perspectives are diverse and uncertainties associated with the decisions are high (Funtowicz and Ravetz, 2003). The post-normal paradigm is an effort towards addressing the complexity of many real world problems based on the acceptance of fundamental uncertainty in science and policy (Petersen *et al.*, 2011). Such uncertainty results in an unpredictability that the normal science as depicted by Kuhn (1996) finds difficult to tackle.

Post-normal science has challenged conventional science in several ways. The main one is that where normal science attempts at establishing the absolute truth for many scientific problems in which the uncertainties and decision stakes are high, the post-normal paradigm identifies such an objective as unachievable (Petersen *et al.*, 2011). It rather introduces quality as a guiding principle towards finding a solution in contrast to the ultimate truth (Funtowicz and Ravetz, 1990) and points out that the evaluation of such quality should not only be done by the expert communities but by whoever shares some stake in the results known as the extended peer community (Laugharne, 2002).

Consequently since no particular expertise can guarantee certainty in the outcome of policies, no scientific expert or public body can claim wisdom and competence about the topic (Petersen *et al*., 2011). This replaces the idea of finding an optimum solution with a resolution that is satisfactory to a larger number of stakeholders.

Although the notion of engagement of stakeholders has been under consideration for a long time (Freeman and Reed, 1983), the insight provided by post-normal science combined with the scientific robustness of complexity approaches has greatly facilitated the advancement of this idea. Such engagement can be done at different levels, and with different degrees of formality: negotiations, co-operative processes, and multi-stakeholders approaches being some of these attempts (Van den Hove, 2000). *Negotiation* as a joint decision making process is a suitable way of incorporating diverse interests of different stakeholders (Savage, 1984).

Negotiation and the need for Artificial intelligence

When it comes to considering pluralistic wishes and diverse viewpoints, negotiation becomes essential (Forester, 1999). Negotiation is a process in which two or more parties dialogue to resolve conflicts or gain an understanding about a certain issue or reach an agreement upon the required courses of action (Pruitt, 1981). The nature of many problems particularly in the context of human and natural systems requires a distributed problem solving perspective and negotiation can be considered as a realisation of distributed problem solving and joint decision making (Davis and Smith, 1983).

It is believed that people's negotiations can be highly deviated from rationality due to individual and competitive biases (Bazerman and Moore, 2008). In many circumstances, negotiations are conducted with readily available information where less noticeable but critical details might be ignored (Neale, 1984). Negotiations are also often considered as fixed-sum and therefore the chance of achieving mutually beneficial trade-offs are neglected (Bazerman *et al.*, 1985). Many disputes could be more efficiently resolved if the negotiation parties were more informed about the possible set of alternatives and had access to a systematic way of evaluating and selecting them (Raiffa, 1982).

In the presence of biases in human negotiation, computer models can facilitate it by processing a wide range of alternatives and examining their outcomes (Oliver, 1997). Software agents as autonomous problem solving entities can support the automation of complex negotiations, by negotiating on the behalf of stakeholders and providing adequate strategies to achieve realistic, win-win agreements (Rahwan *et al.*, 2002).

However, to mimic a complicated process such as negotiation in a computer model, a degree of intelligence needs to be injected into the model. Artificial intelligence (AI) provides the tools required for this purpose. AI is a branch of computer science which aims at developing intelligent machines (Russell *et al.*, 2010). AI techniques have been employed in several disciplines from sociology and psychology to economics and biology (Poole *et al.*, 1998). Negotiation is a process in which AI techniques can be helpful. Having a distributed nature, negotiation demands a high level of intelligence (Davis and Smith, 1983), which can be embedded into artificial agents using AI techniques. Artificial agents are considered the solution for engineering complex distributed systems (Jennings, 2000; Wooldridge, 1997). Due to its individual-based structure, agent-based modeling (ABM) has become a popular approach for simulating human-like behaviors such as negotiation in a complex environment.

Agent-based modeling as an approach to model negotiation in CHANS

ABM is a computational model that tries to create intelligent machines capable of performing human-like intelligent actions such as reasoning, communication and learning (Marceau, 2008). In an ABM, each element of the system that is called an agent is represented by itself (O'Sullivan, 2004) rather than being represented by an average or being aggregated at the regional or sector level (Berger, 2001). An agent represents any entity of the real world such as an individual, a social group or a biological entity that is situated in some environment and is capable of its own action to satisfy its design objectives (Wooldrige, 2002). Agents are identifiable, autonomous, flexible and goal-directed individuals that interact with each other and which behaviours are managed by predefined rules (Macal and North, 2005; Torrens, 2004). They are identifiable in the sense that they are discrete individuals with unique characteristics; their autonomy implies that in spite of their interactions with each other, they are free to make independent decisions. One of the significant qualities of agents is their flexibility, *i.e.*, they are adaptive (Holland, 1995) and can learn from the environment or previous experiences and change accordingly. Moreover agents are goal-directed; this means that they have objectives to achieve according to their behaviour (Wooldridge and Jennings, 1995). These goals are not limited to some utility functions to be maximized; rather they can involve social or cultural objectives that cannot be presented in a mathematical function.

Castle and Crooks (2006) identified three main advantages of agent-based models. First they are able to model "emergent" phenomena. Parker (2001) refers to emergence as the key component of a complex system and argues that to evaluate the success of the agent-based approach to model a complex system the emergent properties of such a system must be identified. As an example she believes that landscape patterns are an important emergent property of land-use agent-based models, and therefore, that pattern measurement should be used when evaluating the success of such models. As another advantage, the agent-based approach provides a natural environment for modeling. This means that the basic units (agents) are more compatible with human's conceptual perception of real-world phenomena. Their third outstanding quality is their flexibility. This flexibility can be recognized through different qualities, the main one being adaptivity, in the sense that agents can learn from the environment and conform themselves to the situation.

Because agents are intelligent and purposeful and act based on their own interests, values and goals, they are highly suitable for incorporating the influence of human actors in biological systems (Matthews, 2007). Moreover they can assess their situation and make decisions on the basis of a set of rules. They are aware of their environment, can communicate with each other and adapt their behaviour (Beck *et al.*, 2008). Because of these qualities, over the last decade, agent-based models have been increasingly designed to investigate the complex interactions between human and natural systems in applications regarding human-wildlife interactions, land-use change, and natural resource management (Marceau, 2008). This modeling approach is particularly adapted to deal with situations where the agents seek their own benefit in the usage of a limited common resource and where a solution needs to be reached to ensure the sustainability of this resource.

In agents' terminology, negotiation can be defined as "the interactions between agents to achieve a cooperative behavior, ranging from concluding contracts to sharing beliefs" (Guyot *et al.*, 2006). Agent-based negotiation acts as a mechanism that determines a mutual agreement that meets different objectives of stakeholders. It deals with three main topics: negotiation protocol, negotiation object, and agents' decision making models (Jennings *et al.*, 2001). The negotiation protocol is a set of rules that controls the negotiation process. It contains the participants of the negotiation, the negotiation states, the events that change the negotiation state, and the range of actions that should be defined for the participants. The protocol identifies the rules of encounter between negotiation participants (Zhang and Luo, 2008). The negotiation object is the range of issues over which an agreement should be reached. In the simplest case the negotiations are fixed, *i.e*., there is no change in any aspect of the negotiation throughout it. In a more advanced level, the stakeholders may change the values of the issues in the negotiation object (*i.e.*, they can make counter-proposals to ensure the agreement better fits their negotiation objectives). Finally in the most advanced level, the stakeholders might be able to dynamically change the structure of the negotiation. The agents' decision-making models are the tools that the participants use to achieve their objectives. The behavior of the participants should be consistent with the defined protocols that are based on the range of operations that can be performed on the negotiation object.

In an agent-based negotiation process, a large group of agents interact to obtain a mutual agreement on some matter of common interest (Laasri *et al.*, 1992). However the incomplete knowledge and the diverse conflicts present in the nature of an agent-based system prevent the agents from sharing all of their social factors (Wang *et al.*, 2009). The argumentation used in the negotiation process enables agents to exchange information to have a better understanding of each other's preferences, beliefs and constraints (Bench-Capon and Dunne, 2007). This process is particularly successful in dealing with reasoning under incomplete or contradictory information in a dynamically changing environment (Wang *et al.*, 2009).

Land development in the Elbow River watershed as a CHANS

Land management is a good illustration of a CHANS in which numerous stakeholders as social actors interact with a natural landscape. It is a good example of a system that reflects pre-existent biophysical factors such as land cover, geomorphology, hydrology, climate and other natural elements and at the same time mirrors the decisions made by human agents who interact in economic markets and public institutions (Alberti, 2008). The complexity of such interactions due to the non-linear relationships and feedback mechanisms among the elements along with the high influence of human decisions requires the integration of multiple disciplines to tackle land management issues. Like any CHANS, it requires the investigation of human-nature relationships using the appropriate set of tools and approaches described earlier.

The Elbow River watershed in southern Alberta is currently experiencing rapid development in both rural and urban areas (Elbow River Basin Water Management Plan, 2009). The type of land and the intensity of its use will have a strong influence on both the quantity and quality of water that will be available in the future. Therefore in recent years, there have been numerous concerns regarding the sustainability of the watershed (Elbow River Basin Water Management Plan, 2009), which have motivated the selection of the Elbow River watershed as the study area. Furthermore, this study is part of a larger project that aims at understanding the impact of land development on the hydrology of the watershed (Wijesekara *et al.*, 2012; Wijesekara *et al.*, 2013). We believe that engaging stakeholders concerned by land development will yield a more complete understanding of the watershed issues and is an important step toward improving the management of the watershed.

It should also be noted that while the watershed extends throughout several municipalities, which increases the complexity of land and water management issues, yet the main land development targeted in this study is concentrated in the area that is close to Calgary.

Research Objectives

The goal of this study is to incorporate the pluralistic perspectives of stakeholders and facilitate their negotiation process over land development scenarios in the Elbow River watershed considered as a coupled human and natural system. To achieve this goal, the following steps must be done:

- To construct a spatial negotiation support system using an agent-based model embedded in a web-based participatory environment. This modeling system will act as a virtual laboratory and allow the stakeholders to share each other's perspective while evaluating land development scenarios in order to reach an agreement.
- To incorporate a learning component into the negotiation process to better mimic human behavior and facilitate the result of the negotiation.

In each of these tasks a number of research questions were to be answered. In the context of the first task we were seeking to answer the following research questions:

- What is a suitable design for a spatial negotiation support system in the context of land development?
- How does the change in the attitude of the agents regarding their preferences impact the results of the negotiation?

Regarding the second task, finding the answers to the following questions was of interest.

- What is the suitable learning approach for the agents in the context of land development?
- What is the impact of including learning in the negotiation among the agents?

Thesis Overview

The remaining of this thesis is organized as follow. The second chapter describes the spatial web agent-based negotiation support system that was developed to support the stakeholders' negotiation over land development in a web-based participatory environment. Different components of this system are presented along with the architecture design. In particular, the use of a fuzzy analytical hierarchy process (AHP) approach for weighting the agents' criteria in the pre-negotiation phase is described in details. Moreover, the negotiation model and the agents' negotiation behavior are depicted. A hypothetical land development scenario was used to test the functionalities of the proposed system.

The third chapter focuses on equipping the agents with learning capability and evaluating its impacts on the achievement of agreement. After reviewing different learning approaches employed in agent-based negotiation, the Bayesian approach was implemented using a land development scenario based on Rocky View growth management strategy (Growth management strategy, 2009).

Chapter 4 provides an overview of the results and contributions of this thesis and proposes future research avenues.

Copyright

This document is compiled as a manuscript-based thesis.

Chapter Two is an unaltered version of the paper published in the *Journal of Environmental Management* as follows:

Chapter One: Pooyandeh, M. and D.J. Marceau, 2013. A spatial web/agent-based model to support stakeholders' negotiation regarding land development. *Journal of Environmental Management* 129: 309-323.

Chapter Three includes the following paper submitted to *Computers, Environment and Urban Systems* that is currently under revision:

Chapter Two: Pooyandeh, M. and D.J. Marceau. Incorporating Bayesian learning in agent-based simulation of stakeholders' negotiation. Submitted to *Computers, Environment and Urban Systems*.

In both papers, the co-author, Dr. Danielle Marceau, is my supervisor. I am responsible for the interviews with the stakeholders, the model design and development, the coding, implementation and testing of the modeling system, and the writing of the scientific papers. However, I have received comments and suggestions from my supervisor throughout all these steps.

A spatial web/agent-based model to support stakeholders' negotiation regarding land development

Abstract

Decision making in land management can be greatly enhanced if the perspectives of concerned stakeholders are taken into consideration. This often implies negotiation in order to reach an agreement based on the examination of multiple alternatives. This paper describes a spatial web/agent-based modelling system that was developed to support the negotiation process of stakeholders regarding land development in southern Alberta, Canada. This system integrates a fuzzy analytic hierarchy procedure within an agent-based model in an interactive visualization environment provided through a web interface to facilitate the learning and negotiation of the stakeholders. In the pre-negotiation phase, the stakeholders compare their evaluation criteria using linguistic expressions. Due to the uncertainty and fuzzy nature of such comparisons, a fuzzy Analytic Hierarchy Process is then used to prioritize the criteria. The negotiation starts by a development plan being submitted by a user (stakeholder) through the web interface. An agent called the proposer, which represents the proposer of the plan, receives this plan and starts negotiating with all other agents. The negotiation is conducted in a step-wise manner where the agents change their attitudes by assigning a new set of weights to their criteria. If an agreement is not achieved, a new location for development is proposed by the proposer agent. This process is repeated until a location is found that satisfies all agents to a certain predefined degree. To evaluate the performance of the model, the negotiation was simulated with four agents, one of which being the proposer agent, using two hypothetical development plans. The first plan was selected randomly; the other one was chosen in an area that is of high importance to one of the agents. While the agents managed to achieve an agreement about the location of the land development after three rounds of negotiation in the first scenario, seven rounds were required in the second scenario. The proposed web/agent-based model facilitates the interaction and learning among stakeholders when facing multiple alternatives.

Keywords: Agent-based model, Stakeholders' negotiation, Fuzzy analytic hierarchy process, Web access, Land development

Introduction

Coupled human and natural systems are formed through the continuous interactions of humans and their surrounding environment (Liu *et al.*, 2007) and therefore few ecosystems are free of human influence (Monticino *et al.*, 2007). In such systems, both social and biological factors interact in shaping patterns and dynamics (Turner *et al.*, 2007), and neglecting any of these factors yields an incomplete picture (Walsh and McGinnis, 2008). As natural resource management deals with conflicting interests of stakeholders who share the same resources for various purposes, considering different perspectives of the involved actors is important (Reed *et al.*, 2009). This, however, represents a considerable challenge mainly because of the complexities involved in modeling human-like behaviors (Bithell and Brasington, 2009). These complexities are not only caused by the complicated nature of human decision making, but are also related to the interactions of human actors with themselves and their surrounding environment. Therefore, in many computer models developed in attempt at investigating these complex interactions, a community of people are substituted by an average, ignoring different and even conflicting viewpoints involved in that community. To avoid this limitation, a bottom-up modeling approach is desired that facilitates learning among stakeholders by sharing and validating their understanding of the situation in order to reach consensus (Rist *et al.*, 2006).

Agent-based modeling (ABM) has received vast attention in recent years. ABM roots in artificial intelligence (Moulin and Chaib-Draa, 1996) that tries to create intelligent machines capable of performing human-like intelligent actions such as reasoning, communication, and learning (Marceau, 2008). In an ABM, each element of the system is represented by itself (O'Sullivan, 2004) rather than being represented by an average or being aggregated at the regional or sector level (Berger, 2001). Since agents are intelligent and purposeful and act based on their own interests, values and goals, they are highly suitable for incorporating the influence of human actors in biological systems (Matthews *et al.*, 2007; Bousquet and Le Page, 2004; Parrott *et al.*, 2011; An, 2012) and for dealing with situations where a solution needs to be found to ensure the sustainability of a common environmental resource (Li and Liu, 2008; Chion *et al.*, 2011). This is the case in land management where decision making requires negotiation among a variety of stakeholders in order to reach an agreement based on the examination of multiple alternatives (Xiao *et al.*, 2007).

ABMs have therefore been employed in several studies attempting to model stakeholders' perspectives and their negotiation process. We describe these studies from three main perspectives: the modeling practice, the participation level of stakeholders, and the tackling of the imprecision of stakeholders' viewpoints. From the modeling perspective, these studies range from simulation models to optimization approaches. Simulation models are used for modeling social actors' behaviors in terms of their own beliefs and perspectives to show the implications of such actions on the environment and other stakeholders (Valkering *et al.*, 2005; Ligtenberg *et al.*, 2004; Kieser and Marceau, 2011). Optimization approaches on the other hand mostly use mathematical models to find the best set of values for an objective function. The optimization techniques that are commonly used for handling multi-objective problems related to stakeholders' different viewpoints (Brauers, 2004) include integer programming (Gabriel *et al.*, 2006), genetic algorithms (Ducheyne *et al.*, 2006), and evolutionary algorithms (Bennett *et al.*, 2004; Muleta *et al.*, 2005; Xiao *et al.*, 2007). While for some time simulation and optimization approaches were kept separate, recent studies have demonstrated the usefulness of their integration (Bone and Dragicevic, 2009; Bone *et al.*, 2011) and several simulation software packages now include a module that performs some sort of optimization (Fu, 2002). This is particularly popular in economic applications such as supply chain optimization (Gjerdrum *et al.*, 2001; Sinha *et al.*, 2011). Multi-attribute agent-based negotiation where utility functions are defined for each agent that tries to find ways to maximize its utility can be considered as a distributed multi-objective optimization approach (López-Carmona *et al.*, 2009).

In terms of stakeholders' participation, studies range from participatory approaches to automated negotiation models (Huang *et al.*, 2010; Lai and Sycara, 2009). In participatory approaches, the stakeholders are closely involved in the different stages of the modelling exercise including model specification, design, testing, and use (Ramanath and Gilbert, 2004). Companion modeling is a good example of a participatory approach in which the preferences of different stakeholders are taken into account in order to promote collective decision making and bring about shared learning (Bousquet and Trébuil, 2005). In this approach, an ABM is combined with role playing games to enable the stakeholders to fully understand the computer model, validate it, and propose new ideas for its improvement (Barreteau, 2003). Automated negotiation on the other hand is an automated search through a space of potential agreements. Each agent has a portion of the space in which it is willing to make agreements; it rates the points in its space and makes use of this rating to determine the actual agreements it makes (Jennings *et al.*, 2001). The argumentation used in the negotiation process enables agents to exchange information to have a better understanding of each other's preferences, beliefs, and constraints (Bench-Capon and Dunne, 2007).

While some studies have applied a crisp negotiation model for stakeholders (Wanyama and Far, 2007; Wang *et al.*, 2009), a common approach to deal with the imprecision nature of stakeholders' viewpoints is to integrate fuzziness in the model. It can be incorporated at different levels: in the relative importance of stakeholders' constraints, in the mechanisms that govern their decision making, and when representing the stakeholders' inter-relationships. Several studies have used a fuzzy approach to implement the trade-off mechanisms in multi-attribute negotiation models (Kowalczyk, 2002; Lai and Lin, 2004; Luo *et al.*, 2003; Chohra *et al.*, 2010).

The approaches mentioned above have some limitations. A classic optimization approach does not take into account the interactions between the involved stakeholders and is therefore not suitable for modeling the trade-offs between them when they negotiate. On the other hand, due to the complicated nature of human decision making, many simulation models end up using a simplistic model for human behaviors. A participatory approach such as companion modeling requires a high involvement of the stakeholders during all the modeling stages, which is not always feasible. In contrast, a fully automated negotiation model does not provide any means of communication between the stakeholders as the users of the model.

This study attempts to overcome the limitations of these approaches at each end of the spectrum by employing an intermediate solution. First, while an ABM is used in this study as a simulation model, the agents have utility functions and each agent tries to find ways to maximize its utility. Unlike many similar studies that employ a competitive negotiation approach that only considers the agents' self-interest (Guttman and Maes, 1998), this study employs a semi-competitive approach (Luo *et al.*, 2003), in which the agents search for a solution that satisfies all parties but also maximizes their own utility. In this type of negotiation, the proposer agent relaxes its constraints to put forward a new offer that it considers less desirable but satisfies the other agents' requirements. Second, in the pre-negotiation phase (Tsvetinov, 2003) a fuzzy analytic hierarchy process (AHP) (Mikhailov and Tsvetinov, 2004) is used by the agents to convert the linguistic comparison of criteria performed by the stakeholders to fuzzy weights. Third, to facilitate the participation of the stakeholders a web-based application is implemented, which acts as a virtual laboratory where the stakeholders can interact through an accessible, interactive computer environment. This web application requires minimum computer skills and can be accessed from any computer that is connected to the Internet. Using a user-friendly interface specifically designed for this project, the stakeholders can propose different land development plans, share their perspective, and participate in the negotiation process.

This study aims at building a spatial negotiation support system for stakeholders using an agent-based model in a web-based participatory environment. This paper describes the architecture and implementation of the proposed system. Then, its functionalities are tested to simulate the negotiation among four agents using two hypothetical land development scenarios in a region close to Calgary, a fast growing city of one million inhabitants in southern Alberta, Canada.

Methodology

In this section, the study area is introduced along with its significance in the context of land development. In Section 2.3, the components and the architecture of the web agent-based model are described, followed by a detailed presentation of the procedure used to simulate the agents' negotiation in Section 2.4.

Case study

The case study used to demonstrate the applicability of the proposed modelling system is the Elbow River watershed in southern Alberta. The Elbow River, an important tributary of the Bow River, originates from Elbow Lake in the Elbow-Sheep Wildland Provincial

Park in the Canadian Rockies. Passing Bragg Creek, Springbank, and the Tsuu T'ina reserve, it enters the city of Calgary where it merges into the Bow River (Fig. 2.1). The watershed occupies an area of 1200 km^2 and supports several uses including supplying drinking water, irrigation for crops, and various recreational activities. Sixty-five per cent of the watershed is located in the Kananaskis Improvement District while the remaining area is divided among the Municipal District of Rocky View (20%), the Tsuu T'ina Nation (10%), and the city of Calgary (5%) (Elbow River Watershed Partnership, 2012).

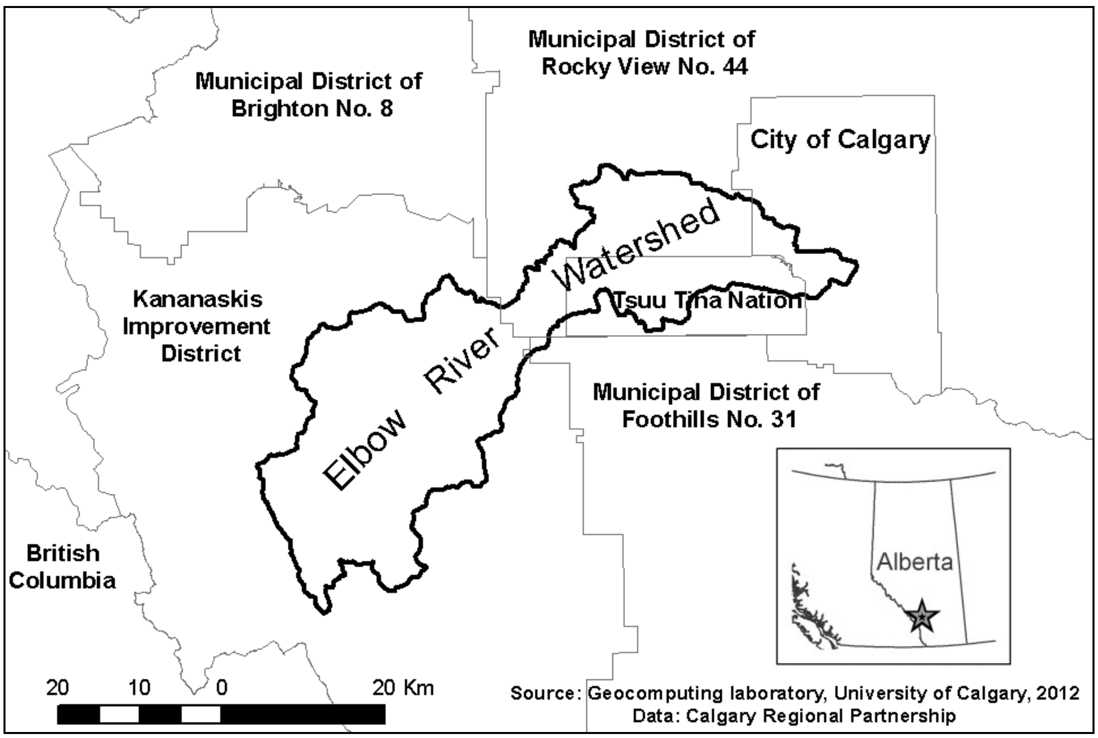


Figure 0.2. Location of the Elbow River watershed in southern Alberta

During the past years, the Elbow River watershed has experienced considerable urbanization pressure due to its proximity to the fast growing city of Calgary. According to Plan it Calgary (2012), an additional 1.3 million people are expected to move into Calgary within the next 50 years, transforming the eastern portion of the watershed into a high potential development corridor (Rocky View County/City of Calgary Inter-

Municipal Development Plan 2012). Since 1989, over 1,000 lots have been created for residential purposes which has caused loss of productive agricultural lands, forest cover, surface water bodies, and increasing levels of water pollution (Central Springbank Area Structure Plan 2001). Due to this fast-paced urbanization, in recent years there have been a number of concerns regarding the deterioration of water availability and quality in the Elbow River watershed. This situation has caused considerable controversy regarding land development in the watershed and has highlighted the need of an approach to facilitate the interaction, discussion, and negotiation among the stakeholders concerned by the impact of land intensification in that area.

Components of the web agent-based model

The modeling system developed in this study includes three main components: a web-based interface, a database management system, and an agent-based model (Fig. 2.2). The users of the system, in particular the stakeholders involved in the project, interact with this system through the web interface. The database contains the information relative to each stakeholder's perspective and behaviour, while the ABM allows their negotiation process regarding proposed land development scenarios.

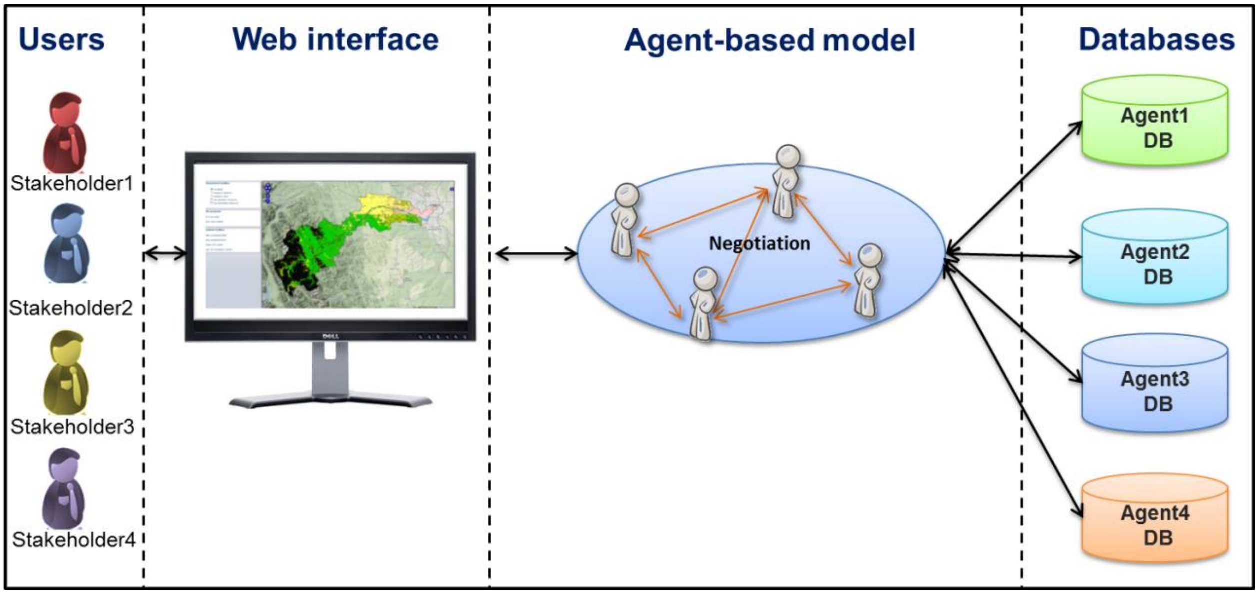


Figure 0.3. A schematic representation of the developed web/agent-based modeling system

Databases: Data collection and storage

The first step in the development of the proposed system is to collect data about the stakeholders' perspectives and behaviour and store them in databases. While the stakeholders evaluate a land development plan based on a number of criteria, the agents need to have access to the data that represent these criteria. The required data were obtained through two main sources: interviews conducted with the stakeholders and existing documents found in different organizations' websites or obtained directly from the stakeholders (Appendix 1). The following documents were used:

- Land-use bylaw (The Municipal District of Rocky View, 2010),
- Environmental Reserve Setback Guidelines (The city of Calgary, 2007),
- Stepping Back from the Water (Alberta Environment, 2012),

- Public Lands Operational Handbook (Alberta Environment and Sustainable Resource Development, 2004),
- Growth Management Strategy (The Municipal District of Rocky View, 2009), and
- Rocky View County/City of Calgary Inter-Municipal Development Plan 2012.

While these documents mainly included the mandates and regulations of each organization, the stakeholders openly discussed their preferences and concerns regarding the land development in the watershed during the interviews. This information was synthesized into criteria employed by the stakeholders to evaluate different scenarios and was used to build the agents' perspective and behaviour in the model. For instance if a stakeholder was concerned about preserving the aquifer, a map of the aquifer was obtained and inputted to the databases to be accessible by the ABM. Therefore when a development plan is submitted, the agent that represents the stakeholder concerned by the aquifer uses the related map to measure to what extent the aquifer is affected by the plan.

Table 2.1 summarizes the evaluation criteria of each agent along with the required dataset that represent these criteria. The first column represents the agent number, the second column lists the criteria of the stakeholders while evaluating a land development plan, and the third column shows the data that were used to measure the goodness of a plan in relation to that criterion. The fourth column indicates the data sources.

Table 0.1. Criteria used by the agents to evaluate a land development plan

Agent number	***Evaluation criterion***	***Dataset***	***Data source***
Agent 1	Reserves	Critical wildlife	AltaLIS
		Crown reserves	AltaLIS
		Environmental Reserves	Rocky View MD
		Environmental impacts	Rocky View MD
		Ecological reserves	AltaLIS
		Forest protection areas	AltaLIS
	Flood hazard	Flood fringe	Rocky View MD
		Floodway	Rocky View MD
		River cross sections	Rocky View MD
	Accessibility	Alberta Road network	Rocky View MD
	Fire	Fire control zones	Rocky View MD
	Oil and gas	Oil and gas reserves	Rocky View MD
	Historic preservation	Historic sites	Rocky View MD

	Biophysical attributes	Biophysical attribute rating	Rocky View MD
Agent 2	Alluvial aquifer	Aquifer map	Rocky View MD
		Aquifer vulnerability index	Rocky View MD
	Groundwater preservation	Groundwater yield	Rocky View MD
	Required setbacks	River stream setbacks	Rocky View MD
		Water wells setbacks	Rocky View MD
Agent 3	Parks and recreation sites	National parks	AltaLIS
		Wild land parks	AltaLIS
		Forest recreation areas	AltaLIS
	Wetland	Wetland map	Rocky View MD
		Wetland Impacts	Rocky View MD
	Trails	Trails maps	Rocky View MD
Agent 4	Agricultural	Agricultural maps	Action for agriculture
		Agricultural land capacity	Canada Land Inventory
		Soil erosion risk	Canadian Soil Information System (CanSIS)

This information was stored in the database of each agent that contains the stakeholders' mandates, goals, and preferences along with the spatial data related to them. Since the data were obtained through several sources with different formats, the *ArcGIS* software package was used to facilitate their preparation and handling. The preparation mainly included unifying the maps' coordinate systems to the North American Datum of 1983 and removing the non-developable regions in the watershed, such as the river where development is physically impossible.

PostgreSQL was used as a free and open source object-relational database management system (ORDBMS) to store and manage these data. Apart from being free, the main reason for this selection is the spatial capabilities provided by *PostGIS*, an open source software program that adds support for geographic objects to the PostgreSQL database. Another reason is that the PostGIS implementation is based on optimized "light-weight" geometries and indices, which reduces disk and memory footprint. PostGIS follows the *OpenGIS* "Simple Features Specification for SQL" (PostGIS, 2012). The communication between the agents and the spatial data stored in the databases were enabled by PostGIS through SQL specifications. The data were stored on different servers to simulate the case where each stakeholder stores his data on its own server. During the simulation process each agent communicates with its respective database on its designated server.

The web interface

All users' interactions with the model are done through a web interface designed to hide the complexity of the various required models and software while allowing interactive access to a range of spatial analysis and visualization functions. These interactions include submitting a new land development plan, comparing the evaluation criteria, inputting/updating the measures of the criteria, inputting the negotiation parameters, and receiving the results of the negotiation. A land development plan is a schematic representation of a land development that is drawn by the user. At this point of our study, this plan is not a detailed map of the development; it mainly describes the location and dimensions of the development.

A set of online GIS tools are provided to the stakeholders so that they can easily draw a new land development plan on the screen and store it to their respective databases. This is made possible using the *OpenGeo* web mapping architecture. This architecture contains three main components: *Openlayers* as an open source JavaScript library for displaying spatial data in web browsers, *Geoserver* as an open-source application server written in Java that allows the users to share and edit geospatial data, and PostGIS that provides spatial functionalities to the PostgreSQL database.

The components of the web interface were developed using Oracle ADF faces and functionalities were added to the client side using JavaScript. To protect the privacy of the stakeholders' data, password protected pages were created and the access level were defined for each stakeholder. Figure 2.3 provides a snapshot of the land development proposal web page. Using basic editing functionalities, the user is able to create a new land development plan by drawing a polygon on the screen. All the changes made at this stage are stored in the stakeholder's respective database to be accessible to the agent-based model.

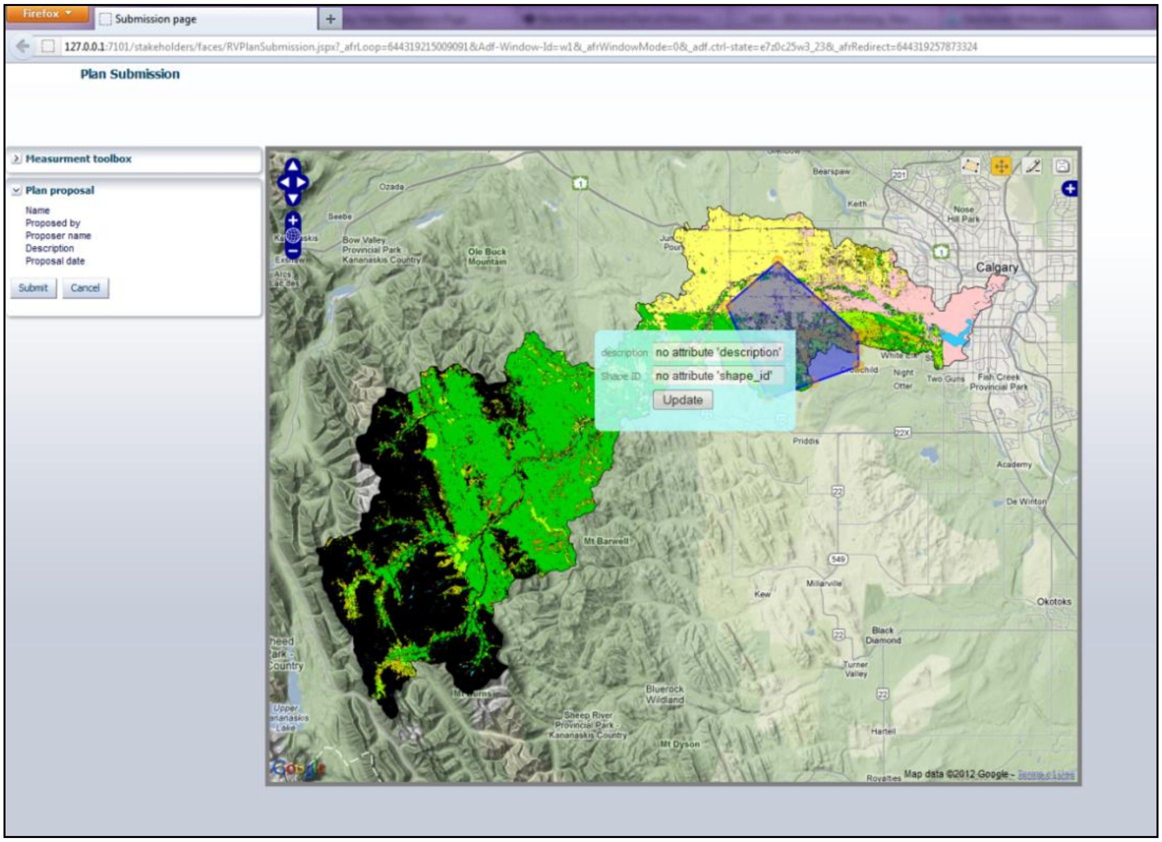


Figure 0.4. Illustration of the land development proposal web page

Another web page was developed to allow the stakeholders to update and rank the measures related to their criteria. The stakeholders can accept the values stored in the model or they can revise them. They are asked to give a value between 1 and 10 to the range of possible values for each measure generated automatically by the model. For example, let's consider a stakeholder who is concerned about the quantity of agricultural land that is affected by a proposed development. This quantity can vary from zero, where no agricultural land is affected by the development to a case where the whole development is located inside the agricultural region. Based on this interval, different ranges of values are generated by the model and the user can grade them according to his/her preferences. Figure 2.4 illustrates this example. The possible range of values for the quantity of agricultural land (expressed in m^2) affected by a proposed land development is calculated by the system. The user is asked to classify this range into a number of categories and grade them based on a scale of 1 to 10. As can be observed in this figure, a stakeholder can allocate a similar rank to several categories based on his perspective.

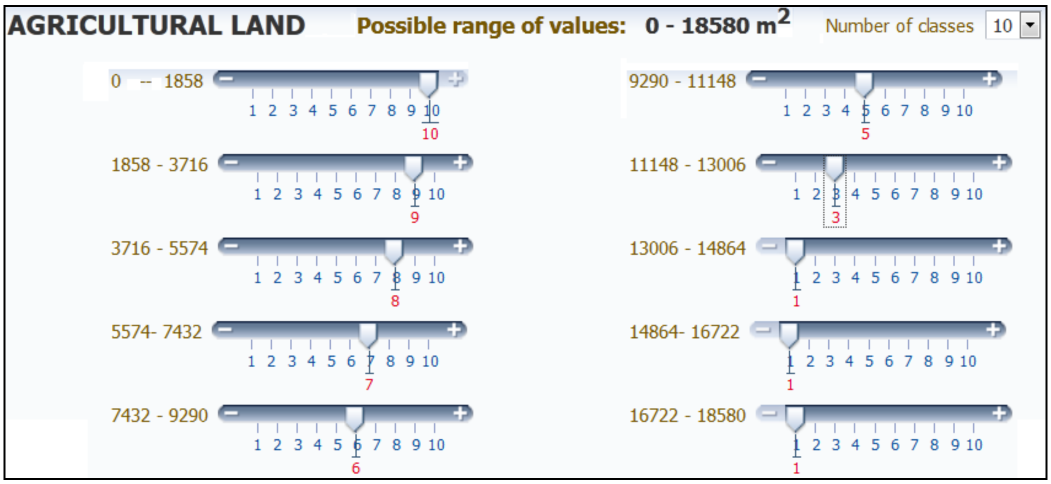


Figure 0.5. A snapshot of the page designed for grading possible values of criteria by the stakeholders

The agent-based model

In this study, four stakeholders were modeled as agents, being respectively a representative of a municipality, a non-profit organization dedicated to various watershed quality concerns, an institute focused on agriculture issues in the watershed, and an agent representing the citizens‘ perspectives. These stakeholders do not represent all the relevant perspectives regarding land development in the watershed; they have been selected to demonstrate the feasibility of the modeling system in its first phase of development. The ABM aims at simulating the stakeholders' negotiation regarding the land development in the watershed.

Although agent-based modeling has been widely used to simulate stakeholders' interactions, few studies have tried a systematic integration of agent and web technologies (Pokahr and Braubach, 2007). This study attempts to do so by employing a model/view/controller model software architecture (MVC) (Leff and Rayfield, 2001) that allows multiple views of a model object (Campos and Hill, 1998). This makes it a good choice for an ABM where several perspectives must be represented. Figure 2.5 illustrates the architecture of the proposed system. Additional details are provided in Appendix 2.

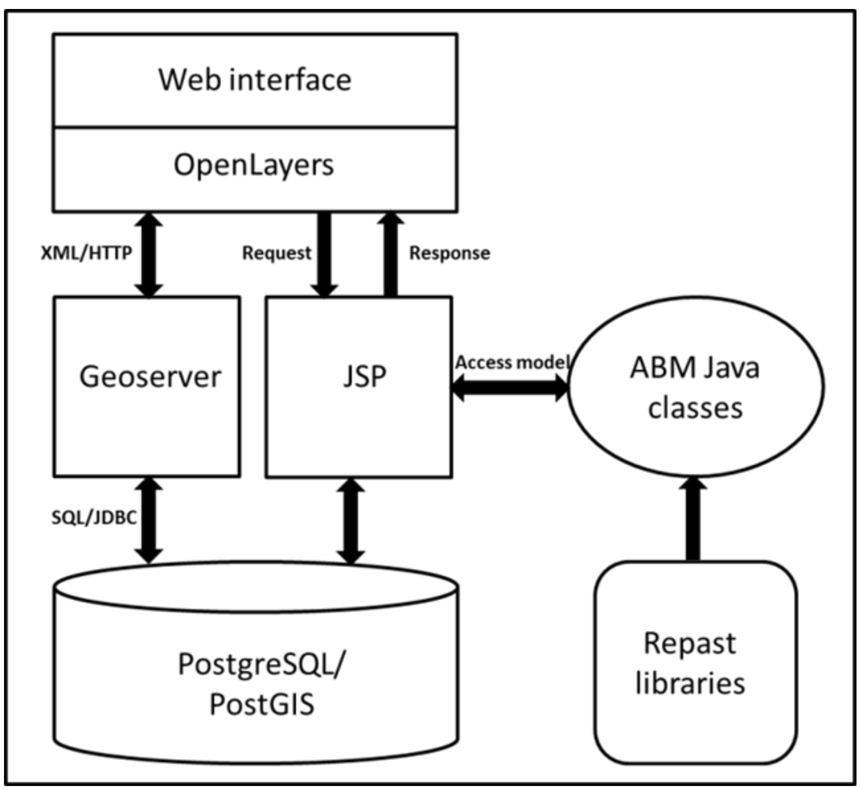


Figure 0.6. System architecture

All the interactions of the user with the ABM are performed through the JSP page. The browser sends a request to the JSP page, which receives it and communicates with the ABM module. The agents of the model are classes developed in Java that have access to the *Repast Simphony* libraries. Repast Simphony is a widely used open source Java based ABM toolkit (Repast website, 2012). After performing the required actions, the ABM communicates with the JSP page that finally returns the requested results to the web interface. The complexity of this design is hidden behind an easy-to-use web interface that facilitates stakeholders' interaction with the model.

Negotiation among agents

In this section, the details regarding the agents' negotiation are presented. The negotiation problem is first formally described, followed by a presentation of the fuzzy approach and the negotiation algorithm that were used. The functionalities of the proposed system were tested using two hypothetical land development scenarios. Of particular interest was to evaluate whether the negotiation algorithm proposed in this study facilitates the consensus among the agents or not. The model was run with four agents and the objective was to find the location which satisfies all four agents to a predefined level of satisfaction. A minimum satisfaction of 60% was considered in this case; this number is a hypothetical value and it does not need to be the same for all agents. In a real case scenario, this number will be selected by the stakeholders. Since the objective here is to test the functionalities of the model, hypothetical values were inputted.

Negotiation problem

The negotiation problem to be solved is summarized in Table 2.2. It is defined as having three agents, *{a, b, c}* negotiating with an agent called the *proposer agent*, *p* over different land development plans in order to find a location that maximizes the profit for the proposer agent and also makes all other agents satisfied to a certain level, *Q* $\{q_1, q_2, q_3\}$. Each agent $i \in \{a, b, c, p\}$ has a set of criteria $j \in \{1,2, \dots, n\}$ for evaluating a land development; w_j^i depicts the weights they assign to these criteria and therefore $V^i(x) = \sum_{1 \le j \le n} w_j^i \cdot V_j^i(x_j)$ is the utility function for each agent, $V_j^i(x_j)$ is the normalized value of the agent's satisfaction at location x for criterion j.

The proposer agent is seeking the maximum profit while the other agents need to meet a certain satisfaction level. The set of alternatives $X = (x_1, \dots, x_n)$ comes from the proposer agent which in this case is the set of possible locations for the land development.

What we are seeking in this negotiation is:

$$\max_{x} V^p(x) = \sum_{1 \le j \le n} w_j^p \cdot V_j^p(x_j)$$

s.t. $V^a(x) > q_1$ *and*

$V^b(x) > q_2$ *and*

$V^c(x) > q_3$

Table 0.2. Components of the negotiation problem

Agents	$i \in \{a, b, c, p\}$
Criteria	$j \in \{1,2, \dots, n\}$
Importance of criteria *j* for agent *i*	w_j^i
Alternatives	$X = (x_1, \ \dots, \ x_n)$
Utility function for agent *i*	$V^i(x) = \sum_{1 \le j \le n} w_j^i \cdot V_j^i(x_j)$
Negotiation goal	$\max_{x} V^p(x) = \sum_{1 \le j \le n} w_j^p \cdot V_j^p(x_j)$ s.t. $V^a(x) > q_1$ *and* $V^b(x) > q_2$ *and* $V^c(x) > q_3$

Pre-negotiation phase: Weighting the criteria

An AHP is used as a multi-criteria decision analysis (MCDA) approach to identify the comparative weights of the criteria associated to each stakeholder. MCDA is an approach that is used in agent-based modeling to deal with mixed sets of quantitative and qualitative data, including expert opinions. It is an appropriate tool for analyzing complex problems such as those typically found in natural resource management (Mendoza and Martins, 2006). To avoid assigning crisp values to their weights that might not adequately reflect their perspectives, the stakeholders are asked to compare their own criteria using linguistic expressions. Figure 2.6 shows the web page that was designed for the criteria comparison. Each row on this page contains three drop down menus. The left and right menus list the criteria, while the one in the centre contains the verbal statements that can be used to compare them, two at a time.

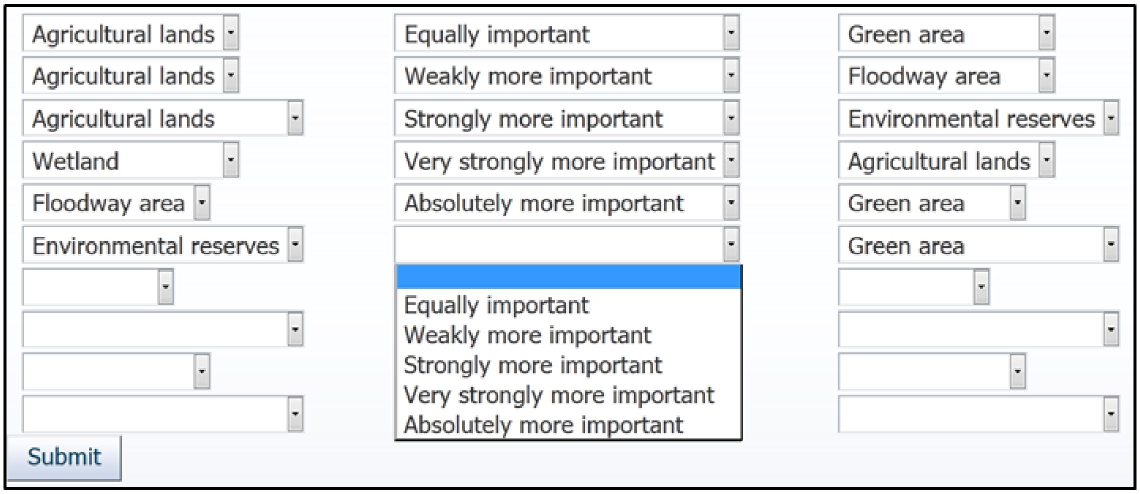


Figure 0.7. Linguistic comparison of stakeholders' criteria

The fuzzy weights obtained at this stage are further used in the negotiation of the agents to adjust their attitudes. After comparing his/her criteria, the user is permitted to submit a land development plan using the web interface, along with three parameters. The first one is the dimension of the search space, expressed as distance in meters. By depicting this dimension, the user conveys how flexible he/she is with the location of the plan. The second parameter is the search interval, expressed as the distance in meters between two consecutive search locations. The third parameter is the user's minimum satisfaction percentage. The reason for applying such a minimum is to avoid a very high satisfaction for one stakeholder and a very low satisfaction for the other ones. The use of linguistic expressions by the stakeholders is advantageous for two reasons: first a crisp assignment of weights that is not desirable is avoided and second these expressions can be further employed in the negotiation process.

After receiving the land development plan and the negotiation parameters, the ABM starts the negotiation in a step-wise manner. This step-wise simulation is performed using the scheduled methods of the Repast Simphony Java libraries. At each time step, a new location for land development is evaluated by the agents against their criteria. To perform this evaluation, each agent connects to its database and performs several spatial and non-spatial analyses on the proposed plan using PostGIS and Repast Simphony functionalities. For example if the agent's criterion is to respect a setback from the river, the agent calculates the distance of the plan from the river boundary to obtain an evaluation of the plan from this point of view. When the numerical values for these evaluations are calculated, since they are expressed in different scales, they are normalized to provide a uniform scale for judgment. All values were transformed to a scale between 0 and 1 using the following equation:

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \text{(Equation 2.1)}$$

Then each agent performs a fuzzy AHP operation on the results to prioritize its criteria and sort the locations based on their weight. AHP is an extensively used technique for multi-criteria decision making (Saaty, 2008). The basic idea behind the AHP is structuring the problem into a hierarchy of levels where each level consists of a number of elements that can be compared to one another, two at a time. The AHP uses these comparisons to prioritize the elements of the hierarchy. Although the AHP approach is widely applied for several years, in many cases the decision maker's preferences are uncertain and fuzzy (Mikhailov, 2003) and it is being criticized for neglecting the vagueness of the human thinking (Deng 1999). To avoid assigning crisp values to the stakeholders' preferences, they can be expressed as fuzzy sets or fuzzy numbers (Zadeh, 1965).

According to Zadeh's mathematical theory, a fuzzy set $\tilde{N}$ is a triangular fuzzy number that can be expressed as (l, m, u) where m is the most possible value and l and u are the lower and the upper bounds. This number has a linear piecewise continuous membership function $\mu_{\tilde{N}}(x)$ with the following characteristics (Dubois and Prade, 1980):

1. A continuous mapping from $\Re$ to the closed interval $[0,1]$;
2. $\mu_{\tilde{N}}(x) = 0$ for all $x \in [-\infty, l]$ and for all $x \in [u, +\infty]$;
3. Strictly linearly increasing on $[l, m]$ and strictly linearly decreasing on $[m, u]$;
4. $\mu_{\tilde{N}}(x) = 1$ for $x = m$.

The fuzzy AHP process workflow contains four main steps:

1. Fuzzifying the crisp pairwise comparison matrix (PCM)

After the user submits the pairwise comparison of his criteria by verbal judgments, the pairwise comparison matrix of criteria is built using Table 2.3. In the first step, the crisp PCM $A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$ is fuzzified using the membership function to obtain the fuzzy PCM:

$$\tilde{A} = \{\tilde{a}_{ij}\} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix}, \qquad \text{(Equation 2.2)}$$

where $\tilde{a}_{ij}$ is a fuzzy number and $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

Table 0.3. Scales in pairwise comparisons (Adapted from Saaty, 2008)

Intensity of importance	*Verbal judgment of preference*
1	Equally important
3	Weakly more important
5	Strongly more important
7	Very strongly more important
9	Absolutely more important

1. Fuzzy extent analysis

Fuzzy extent analysis is applied to get the fuzzy decision or performance matrix $(\tilde{X}_i)$ and fuzzy weights $\widetilde{W}$.

$\tilde{X}_i or\ \widetilde{w_j} = \frac{\sum_{j=1}^{k} \tilde{a}_j}{\sum_{i=1}^{k}\sum_{j=1}^{k} \tilde{a}_{ij}}$ (Equation 2.3)

where $\tilde{a}_{ij}$ is a fuzzy number.

$$\tilde{X}_i = \begin{bmatrix} (x_{11l} x_{11m} x_{11u}) \\ (x_{21l} x_{21m} x_{21u}) \\ \vdots \\ (x_{ijl} x_{ijm} x_{iju}) \end{bmatrix} \qquad \text{(Equation 2.4)}$$

This will yield the fuzzy weighted performance matrix $\tilde{P}$.

$$\tilde{P} = \tilde{X}_i * \tilde{W} = \begin{bmatrix} (w_l x_{11l} w_m x_{11m} w_m x_{11u}) \\ (w_m x_{21l} w_m x_{21m} w_m x_{21u}) \\ \vdots \\ (w_m x_{ijl} w_m x_{ijm} w_m x_{iju}) \end{bmatrix} = \begin{bmatrix} P_{1l} P_{1m} P_{1u} \\ P_{2l} P_{2m} P_{2u} \\ \vdots \\ P_{il} P_{im} P_{iu} \end{bmatrix} \quad \text{(Equation 2.5)}$$

where $\tilde{X}_i$ is the fuzzy performance matrix and $\tilde{W}$ contains the fuzzy weights.

When this stage is completed, the total weighted performance matrix for each alternative is obtained.

2. Alpha cut analysis

To make a crisp choice among the alternatives, the alpha-cuts-based method is needed for checking and comparing fuzzy numbers (Wang, 1997). The alpha cut is determined to account for the uncertainty in the fuzzy range chosen.

$$\tilde{P}_\alpha = \begin{bmatrix} [p_{1l\alpha}, p_{1r\alpha}] \\ [p_{2l\alpha}, p_{2r\alpha}] \\ \vdots \\ [p_{il\alpha}, p_{ir\alpha}] \end{bmatrix} \quad \text{(Equation 2.6)}$$

where l and r represent the left and right value of the interval set and $\alpha \in (0,1]$.

Two values are obtained, namely Alpha_Left (minimum range) and Alpha_Right (maximum range).

$$\alpha_{Left} = [\alpha * (Middle_{fuzzy} - Left_{fuzzy})] + Left_{fuzzy} \quad \text{(Equation 2.7)}$$

$$\alpha_{Right} = Right\_fuzzy - [\alpha * (Right\_fuzzy - Middle\_fuzzy)] \quad \text{(Equation 2.8)}$$

3. Lambda function and normalization of crisp values

The values obtained through the alpha cut analysis need to be converted into a crisp value. This is done by applying the Lambda function that represents the attitude of the agent.

$$Crisp_{Value} = \lambda * \alpha_{Right} + [(1-\lambda) * \alpha_{Left}], \qquad \text{(Equation 2.9)}$$

where λ represents the agent's attitude.

$C_{\lambda} = \lambda * p_{r\alpha} + (1-\lambda) * p_{l\alpha}$,(Equation 2.10)

where $\lambda = [0,1]$ and equation 10 is the parametric description of equation 2.9.

The final step is to normalize the crisp values:

$$C_{\lambda} = \begin{bmatrix} C_{1\lambda} \\ C_{2\lambda} \\ \vdots \\ C_{i\lambda} \end{bmatrix} \qquad \text{(Equation 2.11)}$$

$$\widetilde{C_{\iota\lambda}} = \frac{c_{i\lambda}}{\sum c_{i\lambda}} \qquad \text{(Equation 2.12)}$$

where $\widetilde{C_{\iota\lambda}}$ is the normalized crisp value.

As it will be described in Section 2.3.3, the Lambda, known as the optimism index (Promentilla *et al*., 2008), plays an important role in the negotiation algorithm proposed in this study. In the negotiation process, the agents change their attitude by changing the Lambda value to provide some room for negotiation and reach an agreement.

Negotiation algorithm

After completing the pre-negotiation phase (Section 2.3.1), the fuzzy weights for all agents are calculated. To start, a land development plan along with a number of parameters (described in Section 2.3.1) is proposed by a user (stakeholder). This is the only stage that requires an input from a real world stakeholder. In the all subsequent stages the agents act on behalf of the stakeholders. For the purpose of this paper, a hypothetical land development plan is inputted and one of the agents, referred to as the proposer agent, is selected to act on behalf of the proposer of the land development plans. A negotiation session consists of a negotiation between the proposer agent and all other agents.

The negotiation algorithm applied in this study consists of five main steps (Figure 2.7).

1) First, the proposer agent receives the land development plan and the area that its respective stakeholder is willing to negotiate over. It scans that area and selects the optimal location based on its stored criteria. The proposer agent then offers this location for development as the initial negotiation proposal.

2) The three other agents receive and evaluate the proposed location for land development.

3) If a minimum satisfaction for the three agents is reached, the process is ended and the result is returned to the web interface.

4) If an agreement is not reached, the negotiation continues. The three agents change their attitude regarding the selection of the desired location. Such changes in the agents' attitude are made possible through changing the fuzzy weights. The unsatisfied agents seek the set of weights that increases their utility function. This is done by trying different Lambda values and selecting a new set of weights in the acceptable range of fuzzy weights, *i.e.*, more weight is given to one criterion by the agent and therefore the weight

given to another criterion is reduced accordingly. This enables the agent to investigate all possible sets of weights and observe how it affects its utility function. The changes in the weights may increase or decrease the utility function. If a set of weights makes the outcome of the utility function satisfactory to that agent, it reports to the proposer agent that the location is acceptable. In other words the changes in the agents' attitude have made the agreement possible. This procedure is repeated for all unsatisfied agents.

5) If the changes in the weights of one or more unsatisfied agents did not satisfy them, the proposer agent has to propose the next best location and the negotiation goes back to step 2. This process continues until a location that guarantees minimum satisfaction to all agents is found. If the proposer agent runs out of proposals, the users have the option of changing their minimum satisfaction values or ending the negotiation with the result that makes the majority of the agents satisfied.

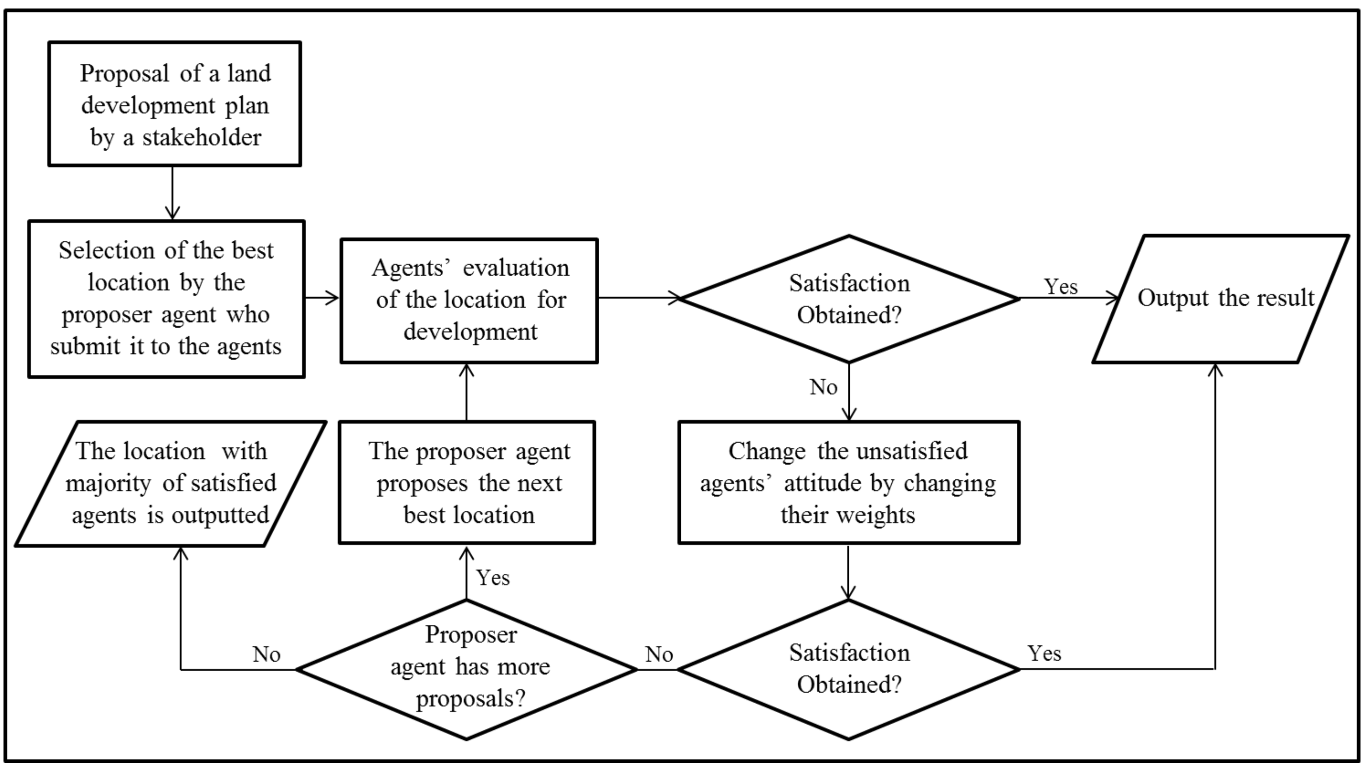


Figure 0.8. Flowchart of the agents' negotiation process

Agents' behavior

Four agents were modelled in this study. Three have the same behaviour while the proposer agent has a different behaviour.

The proposer agent performs the following set of actions {*receive, search, evaluate, select, verify, propose, identify, report*}:

- *receive:*

The proposer agent receives the land development plan along with a number of parameters from the stakeholder through the web interface.

- *search:*

The proposer agent searches the acceptable search area to find the optimum location and returns that location.

- *evaluate:*

Please refer to the *evaluate* action of the other agents described below.

- *select:*

The proposer agent selects the optimum location among the possible set of alternatives.

- *verify:*

In the initial step when a development plan is submitted by a stakeholder, the proposer agent verifies that the proposed location is developeable; a similar verification is done by the proposer agent for all the subsequent proposals made by itself in the negotiation stage. Water, rock, road, green public lands (Public Lands Operational Handbook, 2004) and Tsu T'ina nation land were considered undevelopeable throughout these stages.

- *propose:*

The proposer agent proposes a location to all other agents.

- *identify:*

The proposer agent identifies the unsatisfied agent(s).

- *report:*

The proposer agent reports the result to the web interface and ends the negotiation. The result can be success or failure of the negotiation.

The other three agents (agent 1, agent 2 and agent 3) perform the following set of actions {*receive, evaluate, alter, respond*}:

- *receive:*

The agents receive the proposals from the proposer agent.

- *evaluate:*

All agents of the model are equiped with behaviours and data access so that they can evaluate a land development plan on behalf of the stakehoders they represent. Such behaviors are provided to the agents using a number of spatial analytical capabilities. The agents have access to several GIS functionalities such as distance, overlay, neighborhood, and proximity analysis using the PostGIS and Repast Simphony *Geotools*. They employ such functionalities to measure the goodness of a proposed plan based on their stored criteria without having *a priori* knowledge about each others‘ criteria and measures. The numerical measures that are used by the agents to evaluate the development scenarios were obtained through the interviews with the stakeholders and several provincial bylaws and documents stored in the databases and listed in Section 2.2.1.

- *alter:*

The agents can change their attitude in a negotiation session by altering the weights that they give to their criteria. At each round of negotiation, a different set of weights are calculated by the agents and a new satisfaction value is obtained. The result of this alteration of attitude is either accepting or rejecting the proposal.

- *respond:*

The agents respond to the proposal of the proposer agent based on the performed evaluation. This respond can either be the acceptance of the proposal or its rejection.

Negotiation model

Figure 2.8 shows the pseudocode generated for the negotiation model. Here *proposer* represents the proposer agent, *a*,*b*, and *c* represent the three agents, and AGENT refers to the class of agents.

```
proposer.receive();
WHILE TRUE
    proposer.search();
    proposer.evaluate();
    x= proposer.select();
    IF  x IS NOT NULL
        IF  proposer.verify(x) IS ACCEPTABLE
            proposer.propose(x);
            a.receive(x);a.evaluate(x);
            b.receive(x);b.evaluate(x);
            c.receive(x);c.evaluate(x);
            IF   a.respond IS REJECTION OR  b.respond IS REJECTION OR  c.respond IS REJECTION
                AGENT= proposer.identify();
                IF AGENT.alter(x) IS ACCEPTABLE
                    proposer.report() SUCCESS;
                    TERMINATE;
                END IF
            ELSE
                proposer.report() SUCCESS;
                TERMINATE;
            END IF
        END IF
    ELSE
        proposer.report() FAILURE;
        TERMINATE;
    END IF
END WHILE
```

Figure 0.9. Pseudocode of the negotiation model

The available alternatives for the location of land development come from the proposer and the other agents do not have any knowledge about the next possible proposal; in other words, the possible space of alternatives is only known to the proposer agent. Therefore as soon as the proposer agent finds a location that satisfies all other agents, the negotiation stops and an agreement is obtained. This gives the proposer agent an advantage that mimics what occurs in the real world where a land developer seeks to achieve the maximum possible profit. There is no rational argument for the proposer agent to continue the negotiation after a location considered acceptable by the other agents is found.

It also should be noted that finding the location with the highest overall utility for all agents is not the aim of this study. Rather we attempt at simulating the negotiation process in the context of land development where a negotiation does not necessarily involve investigating all possible alternatives, but to satisfy the negotiation objective.

Verification of the modeling system

Since the objective of this paper is to test the functionalities of the proposed modelling system using hypothetical scenarios, a validation of the results by the stakeholders was not intended at this point. To verify that the modelling system is free of errors and that the analyses are performed correctly, an independent, offline procedure was conducted to compare the results. The analyses that were performed by the agents using PostGIS and Repast Simphony were also done manually at each time step using the ArcGIS software package. Then the results were inputted to a MATLAB software package to conduct the fuzzy AHP procedure. Each step of the negotiation was also conducted and the related analyses were performed manually using the ArcGIS software package. Using the same initial values (initial parameters and satisfaction level) the results of the two different procedures yielded the same location as the outcome.

2.3. Scenarios of land development used in the negotiation

Two scenarios of land development were used for the negotiation. In the first scenario, a random location was selected for the proposed land development. The second scenario was designed to investigate how changing the location of the development plan affects the results of the negotiation. This location was intentionally selected close to a region that is considered as highly important to agent 2, *i.e.*, no development in this area was acceptable to this agent, leading to its low utility value. It is expected that as long as the alternatives submitted by the proposer agent will be located near this region, no agreement would be reached by the agents.

Results

Figure 2.9 shows the changes in the agents' satisfaction values (utility values) based on the various weights they assigned to their criteria through the λ value when evaluating three proposed locations of land development corresponding to three rounds of negotiation. As it can be seen for the first location, the minimum satisfaction value that was pre-determined at 60% is not reached for agents 1 and 2, while agent 3 is satisfied with this location.

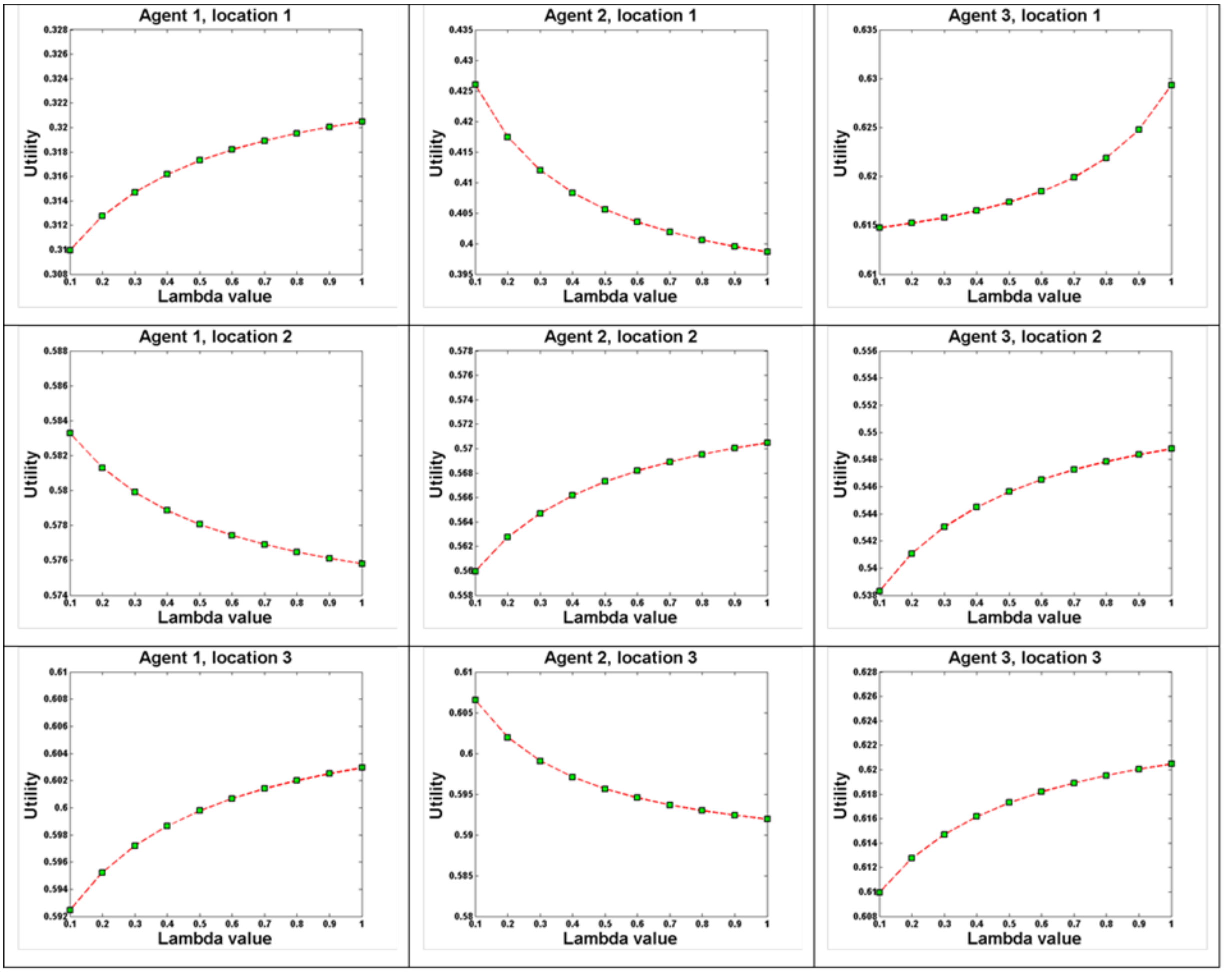


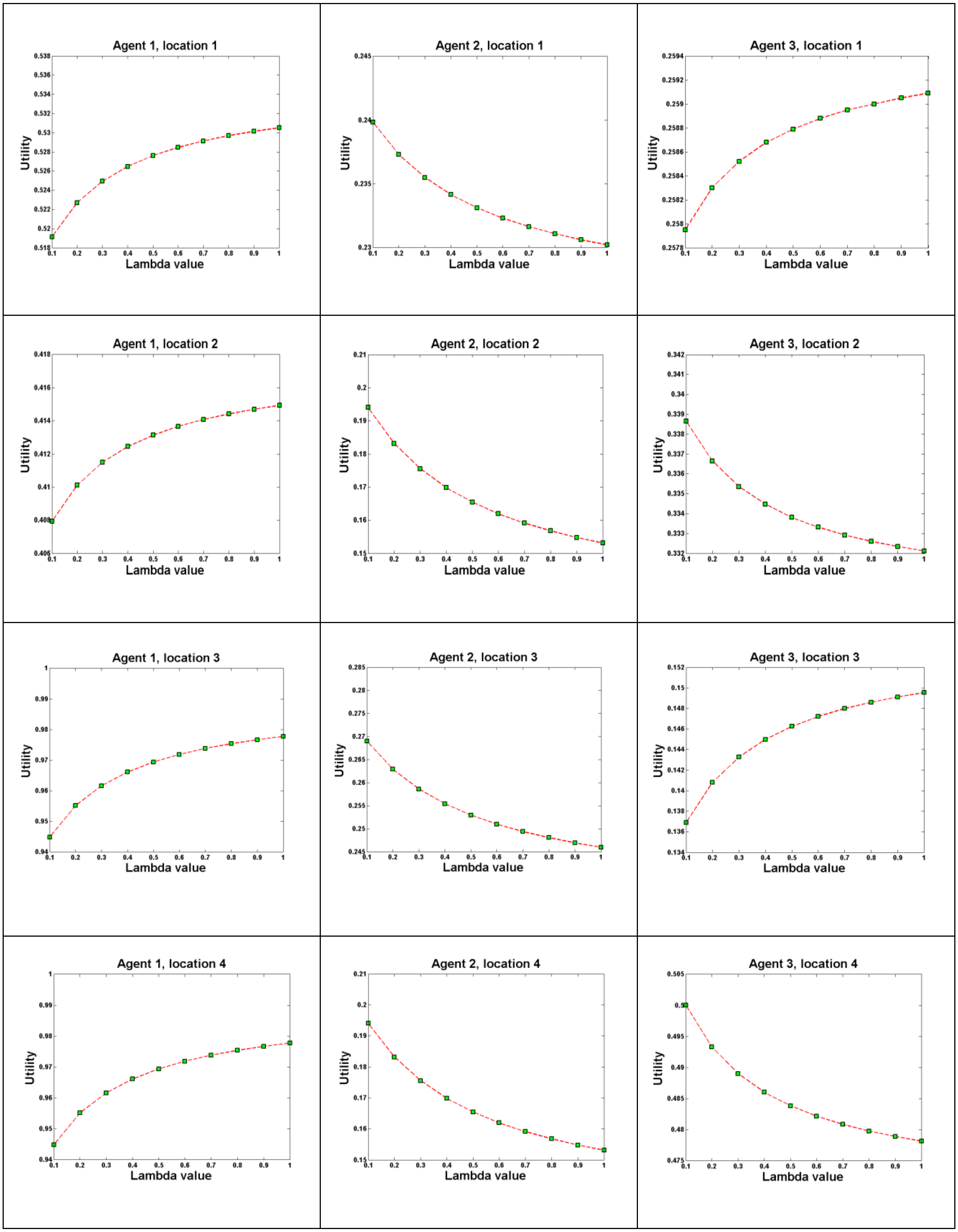
Figure 0.10. Changes in the utility functions of the agents in three rounds of negotiation for the first land development plan

The direction of change in the utility of the agents by modifying the λ value can be positive or negative; therefore as soon as an agent senses a decreasing utility function, it stops the process and reports to the proposer agent that the negotiation over the location will not lead to an agreement. On the other hand as soon as the agent reaches the minimum satisfaction level it reports to the proposer agent that the location under negotiation is acceptable. This can be observed in the second round of negotiation (Fig. 2.9), in which the next best location was proposed by the proposer agent (agent 4).

Although this location is more satisfactory to agent 1, yet it is below the minimum satisfaction level (60%) of all agents. Also while the changes in the λ value increases the utility function of agent 2, it is still below the minimum required. Therefore although location 1 was satisfactory for agent 3, in the second round of negotiation location 2 is below the minimum satisfaction value for this agent and a further round of negotiation is necessary.

The changes in the agents' attitude continue until they find one or more locations that satisfy them to a certain predefined level. In this hypothetical scenario, after three rounds of negotiation, the proposed location for land development satisfies all agents to a certain level, which was 60% in this case.

Figure 2.10 shows the changes in the utility functions of the agents for the second scenario. As it can be observed, the first six locations are not acceptable for agent 2 due to their proximity to the area that is highly important for this agent. The satisfaction value for agent 1 increases considerably in the third round of negotiation and stays high in the remaining rounds. Agent 3's satisfaction level varies from 0.1 to 0.5 in the first five rounds of negotiation and reaches the minimum level at the sixth round. As expected the number of rounds of negotiation required to reach an agreement is higher in this scenario. A soon as the proposed development is not located in or near the area considered as very important by agent 2, in the seventh round, an agreement is reached.


Agent 1, location 1
Agent 2, location 1
Agent 3, location 1
Agent 1, location 2
Agent 2, location 2
Agent 3, location 2
Agent 1, location 3
Agent 2, location 3
Agent 3, location 3
Agent 1, location 4
Agent 2, location 4
Agent 3, location 4
Utility
Lambda value

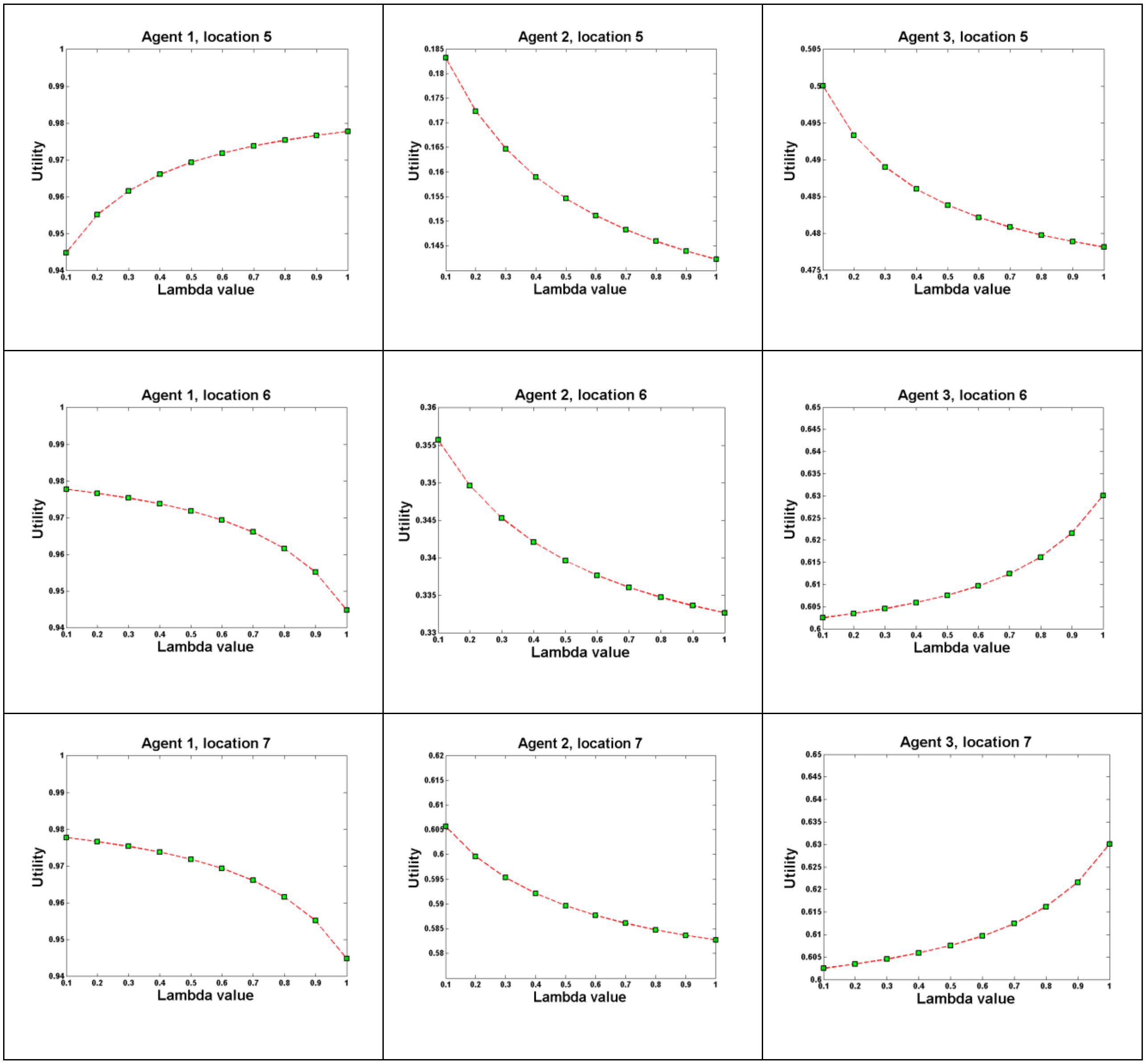


Figure 0.11. Changes in the utility functions of the agents in seven rounds of negotiation for the second land development plan

Conclusions

Considering the considerable current and projected population growth in Alberta, land development is an inevitable phenomenon that might conflict with the preservation of natural resources. Suitable modeling approaches need to be developed to help stakeholders concerned by these issues to find a common area in the decision making space. Despite the fact the decision makers are restricted by regulations and mandates, there is always some room for negotiation within the acceptable framework of regulations. In some cases the opportunities that may rise from the negotiation are unknown to the parties. This study proposes a simulation model to demonstrate that such possibilities can be used by stakeholders to reach agreements. Certainly not all conflicts can be solved by the changes in stakeholders' attitude, but it is a useful way to tackle many conflicts (Forester, 1999) and promote collective learning by revealing possible options to achieve consensus.

This paper describes a web/agent-based spatial negotiation support system designed to support stakeholders' negotiation regarding land development scenarios in south Alberta in order to identify the most satisfactory location for land development according to a set of preferences. To hide the complexity of the various computer models and software that were employed, a web interface was developed to address the needs of users with any level of expertise who can access the system using their web browsers. The model starts with a land development scenario being submitted through the web-based interface as a land-use map with a set of initial values. The stakeholders express the relative importance of their criteria to evaluate this scenario using linguistic expressions. A fuzzy AHP approach is used to translate these comparisons into fuzzy weights to be understandable by the agent-based model and further used in the negotiation process of the agents. The agents perform several spatial analyses to evaluate each scenario by measuring its compatibility with their values and preferences. Using Repast Simphony, they negotiate to reach a compromise about the location of the proposed plan considering each other's values and preferences gathered through interviews with the stakeholders. Throughout the negotiation, the agents change their attitude using the fuzzy nature of the obtained weights to finally reach an agreement that satisfies them.

Since the fuzzy approach is a natural way of modeling trade-offs in a negotiation (Luo *et al.*, 2003), this study also employs a fuzzy approach in the agents' negotiation. However unlike previous studies where fuzzy constraint-based multi-issue negotiation is employed, in this study the importance that the stakeholders assign to their criteria (constraints) is considered fuzzy rather than the criteria themselves. Therefore we focus on the fuzziness in the stakeholders' attitude and not the fuzziness in the measures that they employ to evaluate a land development plan. Moreover in similar fuzzy negotiation models, the agents have a very simple assessment model, while in this study the agents perform several spatial analyses during the negotiation process to evaluate a proposal.

Few studies have attempted to consider environmental factors in the agents' negotiation (Lin *et al.*, 2011; Sorensen *et al.*, 2011; Okumura *et al.*, 2011). To the best of our knowledge, this is the first attempt at designing an agent-based model that explicitly employs spatial measures for evaluating different environmental factors in a multi-issue negotiation problem. Moreover the web-based system developed in this study is an efficient tool to facilitate the stakeholders' participation at different stages of the modeling exercise.

The results presented in this paper demonstrate the applicability of the proposed methodology and the functionalities of the system. Two hypothetical scenarios were tested: one that uses a random location for land development and one that uses a location considered very important for one of the agents. The results demonstrate that the length of the negotiation varies with the location of the development plan in relation with the preferences expressed by the stakeholders. While in many real world cases, the preferences of less influential stakeholders are underestimated, in this study the perspectives of all agents are taken into account. Although the proposer agent has the advantage of selecting the alternatives based on its own utility, a minimum satisfaction level must be reached for all agents involved in the negotiation. Moreover the results illustrate that the changes in the attitude of the agents help achieving an agreement. While in many real world situations the inflexibility of the stakeholders postpones the agreements, our model enables the stakeholders to observe how their desired land development scenario is perceived by others and to learn about each other's perspectives. They can observe how the changes in their attitude open some room for negotiation, which can lead to an agreement among them.

The model proposed in this study is a prototype, developed with four agents and two hypothetical land development scenarios to test its functionalities and illustrate its potential. Work currently in progress consists in running the model with data corresponding to real land development scenarios to assess the utility of the proposed system in guiding decision making.

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Incorporating Bayesian learning in agent-based simulation of stakeholders' negotiation

Abstract

This paper describes the incorporation of a Bayesian learning algorithm into an agent-based model designed to simulate stakeholders' negotiation when evaluating scenarios of land development. The objective is to facilitate reaching an agreement at an earlier stage in the negotiation by providing the opportunity to the proposer agent to learn his opponents' preferences. The modelling approach is tested in the Elbow River watershed, in southern Alberta, Canada, that is under considerable pressure for land development due to the proximity of the fast growing city of Calgary. Five agents are included in the model respectively referred to as the *Developer agent*, the *Planner agent*, the *Citizen* agent, the *AgricultureConcerned* agent, and the *WaterConcerned* agent. Two types of land development scenarios are evaluated; in the first case, only the geographical location is considered while in the second case, the internal land-use composition is also varied. The Developer agent that is equipped with the Bayesian learning capability attempts to approximate its opponents' fuzzy evaluation functions based on the responses he receives from them at each round of the negotiation. The results indicate that using this approach, an agreement can be reached in fewer number of negotiation rounds than in the case where the Developer agent selects the subsequent offers based merely on its own utility. The model also indicates how the satisfaction of each agent evolves during the negotiation. This information is very useful for decision makers who wish to consider stakeholders' perspectives when dealing with multiple objectives in a spatial context.

Keywords: Agent-based model, Stakeholders' negotiation, Bayesian learning, Fuzziness, Land development

Introduction

Global urbanization and the resulting concerns about land sustainability have generated an urgent need for examining scenarios of land development (Wu, 1996). These scenarios are images of future land-use patterns if certain land development regulations were to be adopted by decision makers (Xiang and Clarke, 2003). They facilitate the investigation of possible land development patterns without bearing the costs of implementing them. While land development scenarios have been in practice for years, it is only in the past two decades that the employment of computer models for creating and evaluating them has become possible. These models vary from GIS functionalities (Joao and Walsh, 1992; Batty and Xie, 1994; Hilferink and Rietveld, 1999; Almeida *et al.*, 2005) to sophisticated computational approaches, such as agent-based modelling (ABM) in which the spatial capabilities of GIS are combined to Artificial Intelligence techniques (Ligmann-Zielinska and Jankowski, 2010; Benenson and Torrens, 2003; Matthews *et al.*, 2007).

ABM, which has roots in Artificial Intelligence, possesses outstanding features for simulating and testing scenarios to support decision making (Mensonides *et al.*, 2008). In ABMs, every entity of the system being investigated is represented as an autonomous function unit rather than being aggregated. The capability of these models to connect heterogeneous individual behaviours to collectively emerging patterns makes them suitable for modeling land development scenarios, which requires considering a pluralistic standpoint towards the problem in hand (Lempert, 2002).

When it comes to incorporating multiple views and coping with pluralistic wishes, negotiation becomes a critical and inevitable process (Forester, 1999). Negotiation is a complex decision-making process where each party autonomously represents its viewpoints and interacts with the other parties to reach an agreement (Jennings *et al.*, 2001). In the context of land development, negotiation can be further defined as a search process in which conflicts among different parties are resolved by finding a feasible alternative. In such a case, negotiation is not just a matter of finding an acceptable deal, but an attempt to maximize all parties' payoffs (Choi *et al.*, 2001). Negotiation typically involves a combination of objective facts along with values and emotions. While humans are well equipped to understand the context and deal with the psychological component inherent to human interactions, they lack the capability of simultaneously handling and interpreting a vast amount of information to reach an optimal solution, particularly when the search space is large and complex.

Agent-based automated negotiation is the research field that tackles this challenge. It refers to negotiation conducted with computer agents using artificial intelligence techniques in which two or more agents multilaterally bargain resources for mutual intended gain (Beam and Segev, 1997). A computer agent is situated in some environment and is capable of flexible problem solving behaviour to fulfil a specific purpose (Jennings *et al*., 2001). It has been demonstrated that negotiating agents may obtain significantly improved outcomes compared to results achieved by humans (Jonker *et al*., 2012).

Different agent-based negotiation models have been proposed (Lopes *et al.*, 2009). *Game-theoretic models* are particularly interesting in the context of land development. In these models, the parties choose a strategy to maximize the negotiation outcome by an iterative exchange of proposals. When the agents compete over some issues and there are conflicts to be resolved, the model is said to be non-cooperative (Li *et al*., 2003). If the preference information of a player is known to all other players, then the game is one with *complete information*; otherwise it is called a game with *incomplete information* (Ausubel *et al*., 2002). In a multi-objective negotiation regarding shared environmental resources such as land, dealing with incomplete information is typically the case.

In the absence of complete information, learning techniques can be used by the agents to acquire knowledge about the other agents' preferences or changes in the environment. Incorporating learning techniques in negotiation offers two main advantages (Gerding *et al*., 2000). First, an agent can adjust its own negotiating strategies to obtain better deals based on its previous negotiation experiences. Second learning can be used to update expectations regarding other parties' strategies. Several learning approaches have been used in agent-based negotiation to facilitate the agreement among the agents. They aim at obtaining a better performance in the future based on the experiences gained in the past (Alpaydin, 2004; Kulkarni, 2012). The selection of the appropriate learning method highly depends on the nature of the problem and the imposed assumptions.

One of the popular learning approaches in agent-based negotiation is Reinforcement Learning (RL). In RL, a numerical performance measure representing an objective is being maximized (Szepesvári, 2010). At each iteration, the agent takes an action that changes the state of the environment; such transition is communicated to the agent through a scalar reward called *reinforcement signal* that evaluates the quality of the transition (Kaelbling *et al.*, 1996). The agent atempts to increase this value by employing a wide variety of algorithms such as *Q-learning*, through a systematic trial and error process. In fact the agents attempt to learn the best action that needs to be conducted at each state. The study of Bone and Dragićević (2010) is a good example of the use of RL to improve the negotiation results in a multi-stakeholder agent-based forest management model. The agents represent forest companies that try to maximize their interests and a conservationist agent that attempts to protect species habitat. RL algorithms are employed to allow the forest company agents and the conservationist agent to learn where harvesting should occur so that their objectives are met.

A common issue with RL is to find a balance between *exploration* that consists in taking sub-optimal actions to discover new features, and *exploitation* that involves using the knowledge currently available about the world (Coggan, 2004). Each action must be repeated several times to obtain a reliable estimate of its expected reward (Kulkarni, 2012). Moreover the temporal aspect is also important because an agent might receive insignificant reward in a long sequence of actions, but finally achieve a high reinforcement at a certain state (Nowé *et al.*, 2012). Generalization is another issue in RL in which a function approximator such as neural network is needed to generalize between similar situations and actions (Boyan and Moore, 1995; Sutton, 1996).

Other learning techniques have been employed in agent-based negotiation. Choi *et al.* (2001) used genetic algorithm to enable an agent to learn its opponents‘ preferences based on the counter-offers received during the previous rounds of negotiation. As expected, this approach requires a large number of rounds to obtain meaningful results. Carbonneau *et al.* (2008) used a neural network to predict the opponents‘ negotiation moves in electronic negotiations. Other than the requirement for a large number of negotiation rounds, the generalizability of the approach presented in this study is also limited.

A promising approach to deal with the issue of learning in agent-based negotiation is Bayesian learning. It is a machine learning method which has roots in mathematical statistics. In this approach, the Bayes‘ rule is employed to update the probabity of an hypothesis based on acquired evidence. In other words, the posterior probability distribution of a hypothesis is computed conditioned to the evidence obtained through new data. It has been demonstrated that Bayesian learning provides the opportunity to learn an opponents‘ evaluation function in a fewer negotiation rounds in comparison with a no-learning scenario (Hindriks and Tykhonov, 2008). Moreover Bayesian learning is not data intensive and can yield noticeable results in a reasonable number of negotiation rounds.

One of the initial attempts to incorporate Bayesian learning in agent negotiation was made by Zeng and Sycara (1996) who developed a sequential decision making model called Bazaar in which the agents were able to learn the opponents‘ preferences. However, the model was not suitable for a negotiation problem in a dynamic environment where the agents‘ actions change throughout the negotiation (Li and Cao, 2004). In another study conducted by Bui *et al*., (1999), agents equiped with Bayesian learning capability work together to book meetings on the behalf of their respective users. When using the learning techniques, accurate predictions are made by the agents about their opponents‘ utility functions resulting in overall better performance.

Ren and Anumba (2002) employed the Bayesian learning approach to facilitate negotiation among participants in a multi-agent system called MASCOT designed for constructing claims negotiation. While it improved the negotiation results, it was conditioned to the fact that the agents could gain enough prior knowledge about their opponents. Buffett and Spenser (2007) examined the effectiveness of Bayesian learning for learning an opponent’s preferences during a bilateral multi-issue negotiation. Using a hypothetical negotiation scenario, they were able to determine the opponents‘ preferences in a few rounds of negotiation.

Jacobs and Kruschke (2011) argue that many aspects of human learning can be captured by the Bayesian approach. The ability of people to learn from limited data can be addressed in a Bayesian framework by strong constraints on the prior beliefs. Moreover the assumptions made in Bayesian models are often expressed as well-defined mathematical expressions which make them easy to examine, evaluate, and modify.

Additionally, since the Bayesian models update probabilities for all possible values of the variables, they yield a distribution over all possible outcomes rather than a fixed point, which enables them to update several competing hypotheses.

This paper describes the incorporation of Bayesian learning in an ABM to simulate the negotiation process of multiple stakeholders regarding land development scenarios. This work is a continuation of a previous study conducted by the authors (Pooyandeh and Marceau, 2013) which aimed at building a spatial negotiation support system for stakeholders using an agent-based model in a web-based participatory environment. While the model adequately captured different aspects of the negotiation process, it lacked the important notion of learning among agents, which is an essential process in real-world stakeholders' negotiation. In this study, our goal is to evaluate the impact of adding a learning component to the achievement of agreement among agents and to examine how it affects the negotiation behaviour of the agents.

Compared to the previous study, the following improvements have been made.

- *Adding an agent:* An additional agent (the Developer agent) was incorporated in the model to bring a new perspective into the negotiation and a more realistic representation of land development in which the developer proposes a scenario. Although there was a proposer agent in the previous study, it was only responsible for making offers and did not have the behaviors of an agent designed to represent a developer in a land development scenario.

- *Incorporating fuzzy evaluation functions:* In the previous study, fuzzy weights, which consider the weights as fuzzy numbers rather than crisp values, were assigned by the agents to their criteria; in this case, fuzziness is also incorporated in the way the agents evaluate land development scenarios to better reflect the uncertainties included in this process.
- *Learning:* In our previous study, the proposer agent made offers to the agents; here called the *Developer* agent, did not employ the knowledge gained through the negotiation to make offers to his opponents; in this study, this agent is equipped with learning capabilities to facilitate the agreement achievement in the negotiation. The preferences of the opponent agents are known to the Developer agent; however the Developer agent attempts to learn the attitude of the opponent agents in regard to their preferences and to make the next offer accordingly.
- *Running the model with real land development plan:* Unlike the previous work in which the location of the land development was hypothetically selected, a real land development plan, based on the Rocky View Growth Management Strategy (2009), is used in the model. Starting with this plan, several land development scenarios are generated and evaluated by the agents.

Methodology

In this section, the study area is introduced along with its significance in the context of land development. In Section 3.2.2, the essential components of the agent-based model are presented and the criteria used by the agents are described. The updated negotiation model and the learning of the agents are described in Sections 3.2.3 and 3.2.4, respectively.

Case study

The case study used to demonstrate the effectiveness of the proposed modelling approach is the Elbow River watershed in southern Alberta (Figure 3.1). The Elbow River, which is an important tributary of the Bow River in southern Alberta, originates from Elbow Lake in the Elbow-Sheep Wildland Provincial Park in the Canadian Rockies. Passing Bragg Creek, Springbank and the Tsuu T'ina reserve it enters the City of Calgary where it merges into the Bow River. The watershed occupies an area of 1200 km^2 and supports several uses including residential and commercial, agriculture and forestry, and various recreational activities. Sixty-five per cent of the watershed is located in the Kananaskis Improvement District and the remaining area is divided among the Municipal District of Rocky View (20%), the Tsuu T'ina Nation (10%) and the City of Calgary (5%) (Elbow River Watershed Partnership 2013).

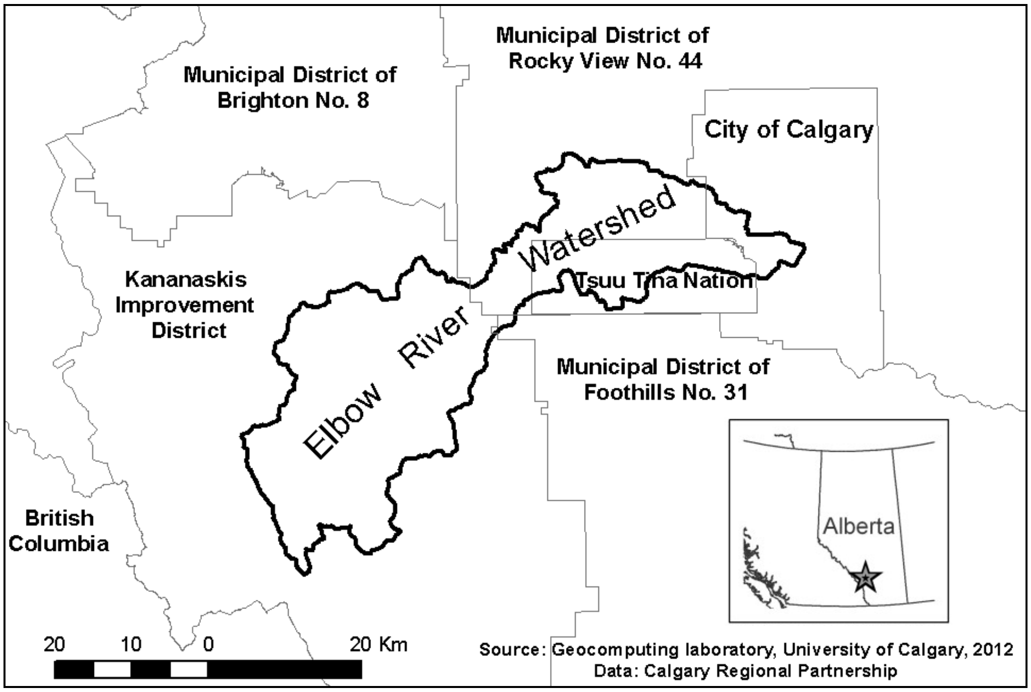


Figure 0.12. Map of the study area

Due to the strong Alberta economy, the city of Calgary has become a major job attractor in the recent years, nationally and internationally. This has resulted in a population increase of 70% between 1988 and 2012 (Civic Census Results City of Calgary, 2012), which has imposed considerable urbanization in and around the city. The Elbow River watershed, located in the western part of Calgary, has experienced high pressure for land development in the recent years, which threatens the integrity of the Elbow River as a sustainable ecosystem (Elbow River Watershed Partnership, 2013). Engaging stakeholders concerned by land development is an important step toward improving the management of the watershed.

The agent-based model

In this section, the details of the agent-based model implementation are described, beginning with the agents and their preferences, followed by the fuzzy evaluation functions of the agents.

The agents and their preferences

The agent-based model includes five agents:the *Developer agent*, the *Planner agent*, the *Citizen agent*, the *AgricultureConcerned* agent, and the *WaterConcerned* agent. The Developer agent represents the developer in a land developement process. This agent plays an important role in the model; he initiates all proposals for development and therefore enters into a one-to-many type of negotiation with the other agents in order to obtain their approval, or in other words gain their satisfaction. This agent tries to maximize its own utility while improving the other agents' satisfaction level to make the land development possible through a collective satisfaction. The utility function of the developer is calculated based on several parameters related to land developement: density, construction cost, land value, road dedication, developed land value, and wetland construction cost (Kieser and Marceau, 2011). These parameters are used by the Developer agent to calculate its utility function every time he has to come up with a new proposal.

The Developer agent aims at increasing the housing density to increase his profit; three densities are considered: low, medium and high density. The second factor considered by the Developer agent is the approximate value of construction cost evaluated at $10000/ m of lot frontage. The third factor is the percentage of road dedication. From experience, the developer determines that approximately 29% of the developable area is dedicated to roads, of which 34% are 22 m wide collector streets and 66% are 15 m wide local streets. The developed land values were obtained using the web pages of real estate agents in the area while the undeveloped land values were obtained using the Rocky View online land assessment tool (Rocky View, 2013). The cost of constructing wetlands varies between $12,000 and $60,000 per hectare (Alberta Government, 2000). The criteria that form the utility function of the Developer agent along with their value and sources are listed in Table 3.1.

Table 0.4. Criteria considered by the developer agent to propose a land development scenario

Criteria	Value	Source
Density	Low, medium, high	Literature
Land value	Variable	Rocky View online land assessment tool (Rocky View 2013)
Road dedication	29%, of which 34% are 22 m wide collector streets and 66% are 15 m wide local streets	Kieser and Marceau (2011)
Construction cost	$10000/ m of lot frontage	Kieser and Marceau (2011)
Developed land value	Variable	Real estate agents in the area
Wetland construction cost	$12,000 - $60,000 per	Alberta Government (2000)

	hectare	

The Planner agent represents the planner in the land development process. In addition to the bylaws and regulations that need to be considered in a land development plan, the Planner agent has preferences that are taken into account in the model. The Citizen agent represents the citizen‘s perspectives regarding land development in the watershed. The WaterConcerned agent represents a non-profit organization dedicated to various water issues in the watershed and the AgricultureConcerned agent represents an institute concerned about the agricultural lands and their preservation. Their preferences are summarized in Table 3.2. This information was collected during interviews with the stakeholders. It is stored in a *PostgreSQL* database to be accessed by the agents of the model. A detailed description of the collection and storage of the data can be found in Pooyandeh and Marceau (2013).

Table 0.5. Criteria used by the agents to evaluate a land development plan

Agents	**Evaluation criteria**	**Datasets**	**Data sources**
Planner agent	Reserves	Critical wildlife	AltaLIS
		Crown reserves	AltaLIS
		Environmental Reserves	Rocky View MD
		Environmental impacts	Rocky View MD
		Ecological reserves	AltaLIS
		Forest protection areas	AltaLIS
	Flood hazard	Flood fringe	Rocky View MD

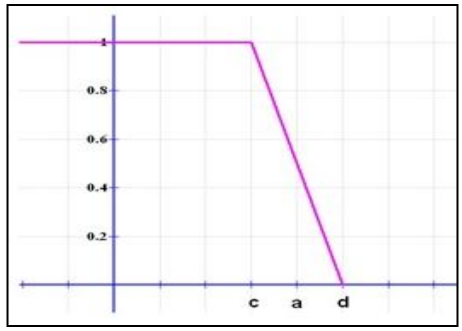
		Floodway	Rocky View MD
		River cross sections	Rocky View MD
	Accessibility	Alberta Road network	Rocky View MD
	Fire	Fire control zones	Rocky View MD
	Oil and gas	Oil and gas reserves	Rocky View MD
	Historic preservation	Historic sites	Rocky View MD
	Biophysical attributes	Biophysical attribute rating	Rocky View MD
WaterConcerned agent	Alluvial aquifer	Aquifer map	Rocky View MD
		Aquifer vulnerability index	Rocky View MD
	Groundwater preservation	Groundwater yield	Rocky View MD
	Required setbacks	River stream setbacks	Rocky View MD
		Water wells setbacks	Rocky View MD
Citizen agent	Parks and recreation sites	National parks	AltaLIS
		Wild land parks	AltaLIS
		Recreation areas	AltaLIS
	Wetland	Wetland map	Rocky View MD
		Wetland Impacts	Rocky View MD
	Trails	Trails maps	Rocky View MD
	Density	Land development plan	Hypothetical
AgricultureConcerned agent	Agricultural	Agricultural maps	Action for agriculture
		Agricultural land capacity	Canada Land Inventory
		Soil erosion risk	Canadian Soil Information System (CanSIS)

The agents‘ evaluation functions

During the interviews with the stakeholders, it was observed that they were unwilling to assign crisp numerical values to their preferences; rather they prefered to assign an interval to the measures that defines a satisfactory land development scenario. A fuzzy approach to capture the preferences of the stakeholders was therefore selected for this study. For each preference that was described by the stakeholders in the interview, a fuzzy membership function was developed. Instead of labeling a value observed for a preference as satisfactory or unsatisfactory, this function assigns a number between 0 to 1 to the degree of satisfaction of the agent with this preference. This fuzzy membership function is called the evaluation function of that preference hereafter.

Let’s suppose a case where the amount of agricultural land affected by a land development scenario a is $c < a < d$ (Fig. 3.2); in this case instead of labeling this amount as completely satisfactory (1) or completely unsatisfactory (0), a value between 0 to 1 is assigned to the satisfaction level of the agent which is shown in figure 3.2. as $e(x)$. Such evaluation functions are defined for the agents during the *pre-negotiation* stage, a step where the evaluation functions of the agents‘ preferences along with the weights assigned to these preferences are calculated. A detailed description of the pre-negotiation stage can be found in Pooyandeh and Marceau (2013).

$$e(x) = \begin{cases} 0, & x > d \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 1, & x < c \end{cases}$$



Based on the information gathered during the interviews with the stakeholders, a fuzzy membership function was obtained and assigned to the preferences of each agent.

The utility of each agent is computed as a weighted summation of the values obtained for each preference, which is:

$$u(S_t) = \sum_{i=1}^{n} w_i e_i(x_i \in S_t) \qquad \text{(Equation 3.1)}$$

where x_i is the value of preference *i* in land development scenario S_t, w_i is the weight assigned to this preference, and $e_i(x_i)$ is the evaluation function for preference x_i. We have considered a fuzzy membership function for each $e_i(x_i)$; therefore the utility of each agent was obtained through a summation of these evaluation functions to generate Equation 3.1.

The negotiation model

Before proposing a scenario to the opponent agents, the Developer agent scans the area of development to find the locations that yield the maximum utility for itself. These locations constitutes the utility iso-curve of the Developer agent. An iso-curve is a curve on which the utility values for the Developer agent are identical (Faratin *et al.*, 2000; Hindriks and Tykhonov, 2008). Any location on this iso-curve corresponds to the maximum possible utility of the Developer agent, but yields different utility values for all other agents. In building the utility iso-curve for the Developer agent, rather than using a fixed value a small interval from this value is considered on the iso-curve. Therefore the iso-curve is created using an interval $[u - \delta; u + \delta]$ rather than the value u. At this point, the Developer agent has two options. The first one is to make offers that are only based on its own utility values; when two locations have the same utility value, the Developer agent randomly selects one of them and proposes it to the agents. This is the approach implemented by Pooyandeh and Marceau (2013). The second option is to employ a learning strategy to reduce the negotiation time and facilitate the agreement achievement. In this paper a learning strategy is used for the proposal of land development scenarios by the Developer agent, which will be discussed in detail in Section 3.2.4.

If no scenarios on the Developer agent's iso-curve satisfies the other agents to a certain level, a concession needs to be made by the Developer agent. This is achieved by scanning the space to find the locations that provide a lower utility for itself but a possibly higher utility to its opponents. Therefore another iso-curve is created by the Developer agent, which contains the utility values lower than the maximum utilities. Then the Developer agent employs the outcome of the learning procedure to make the next offer. In other words it is the developer agent which has to learn from the previous rounds of the negotiation and propose an alternative that accomodates the opponets' perspectives to a higher level. At each step of the negotiation, a concession is made by the Developer agent. This process continues until a location is found that satisfies all agents to a certain level, *i.e.*, the negotiation is successful when an agreement is reached.

A version of the negotiation model is presented as a pseudocode in Figure 3.2. Here the *Developer* represents the Developer agent and *a*, *b*, *c*¸ and *d* represent the other four agents. The Developer agent performs the following set of actions: {*receive, search, evaluate, select, verify, propose, identify, report, buildIsoCurve, learn* and *concede*}. Compared to the negotiation model presented in Pooyandeh and Marceau (2013), the Developer agent is equiped with three additional actions: *buildIsoCurve*, *learn*, and *concede*. Moreover the *select* action is not merely a random selection of a location; rather it includes applying the learnt information and selecting a location based on the other agent's preferences.

- *receive:* The Developer agent receives the land development plan along with a number of parameters from the stakeholder through the web interface.
- *search:* The Developer agent searches the acceptable search area to find the optimum location and returns that location.
- *evaluate:* The agents employ GIS analyses such as proximity, network, and overlay they are equipped with to evaluate a proposal according to their criteria listed in Table 3.1.
- *buildIsoCurve:* Using this action, the Developer agent searches the space and builds an utility iso-curve.
- *select:* The Developer agent selects the optimum location among the possible set of alternatives, not only based on its own criteria but also considering his learnt information.
- *verify:* In the initial step of the negotiation when a development plan is submitted by a stakeholder, the Developer agent verifies that the proposed

location is developable; a similar verification is done by the Developer agent for all the subsequent proposals made by itself in the negotiation stage. Water, rock, road, green public lands (Public Lands Operational Handbook 2004) and the Tsu T'ina nation land were considered undevelopable throughout these stages.

- *propose:* The Developer agent proposes a location to all other agents.
- *identify:* The Developer agent identifies the unsatisfied agent(s).
- *report:* The Developer agent reports the result to the web interface and ends the negotiation. The result can be success or failure of the negotiation.
- *learn:* After each response from the agents, the Developer agent learns from his negotiation experience, the details of which are presented in Section 3.2.4.
- *concede:* Using this action, the Developer agent moves from the higher utility iso-curve to the lower utility iso-curve in order to make an agreement possible.

The other four agents perform the following set of actions: {*receive, evaluate, alter,* and *respond*}:

- *receive:* The agents receive the proposals from the Developer agent.
- *evaluate:* The agents employ the GIS analysis tools they are equipped with to evaluate a proposal according to their criteria listed in Table 3.2.
- *alter:* The agents can change their attitude in a negotiation session by altering the weights they give to their criteria. At each round of negotiation, a different set of weights are calculated by the agents and a new satisfaction value is

obtained. The result of this alteration of attitude is either accepting or rejecting the proposal.

- *respond:* The agents respond to the proposal of the Developer agent based on the performed evaluation. This response can either be the acceptance of the proposal or its rejection.

```
developer.receive();
WHILE TRUE
    developer.search();
    developer.evaluate();
    developer.buildIsoCurve();
    x= developer.select();
    IF  x IS NOT NULL
        IF  developer.verify(x) IS ACCEPTABLE
            developer.propose(x);
            a.receive(x);a.evaluate(x);
            b.receive(x);b.evaluate(x);
            c.receive(x);c.evaluate(x);
            d.receive(x);d.evaluate(x);
            IF   a.respond IS REJECTION OR  b.respond IS REJECTION OR  c.respond IS REJECTION OR  d.respond IS REJECTION
                AGENT= developer.identify();
                developer.learn();
                IF AGENT.alter(x)  IS ACCEPTABLE
                    developer.report()  SUCCESS;
                    TERMINATE;
            ELSE
                developer.learn();
                developer.report()  SUCCESS;
                TERMINATE;
            END IF
        END IF
    ELSE
        developer.report()  FAILURE;
        TERMINATE;
    END IF
    developer.concede();
END WHILE
```

Figure 0.13. Pseudocode of the negotiation model

Bayesian learning

The literature on Bayesian learning is abundant (Mitchel, 1997; Zeng and Sycara, 1998; Gale and Kariv, 2003). After a brief description of the basic concepts, we focus on the application of Bayesian learning in the context of negotiation.

The Bayesian approach provides a mechanism to detemine the propability of a hypothesis conditioned to a set of data (Ellison, 1996). It yields the *posterior* probability based on *a prior* probability and a likelihood function derived from a probability model for the data to be observed. Such probability is computed using the Bayes' rule:

$$P(H|E) = \frac{P(H) \times P(E|H)}{P(E)} \qquad \text{(Equation 3.2)}$$

Here *E* refers to the *evidence* that corresponds to the new data, *H* is the hypothesis that needs to be examined based on the evidence, $P(H)$, which is called the *prior probability* is the probability of the hypothesis before considering the evidence, $P(E)$ is the probability of occurence of E, $P(E|H)$ is the probability of observing *E* given *H*, which is called *likelihood*, and finally $P(H|E)$, called the *posterior probability* is the probability of *H* given *E*.

Due to its solid statistical foundations, the Bayesian approach has been recently used in the context of agent-based negotiation (Buffett and Spenser, 2007; Bui *et al.*, 1999; Hindriks and Tykhonov, 2008; Li and Cao, 2004). We describe here its application in the land development negotiation process. Imagine that the Developer agent has proposed land development scenario S_1 to agent a_1 which is evaluated and then accepted by a_1, but rejected by one or more other agent(s). The Developer agent now needs to make another proposal based on his knowledge from the previous round of negotiation. This knowledge depicts that the land development scenario S_1 with the values $P(P1 = p_1, P2 = p_2 \ and \ ...)$ obtained for the preference set of of agent a_1 is acceptable to agent a_1 but unacceptable to another agent. The Developer agent has land development scenarios S_2, S_3 and S_4 on its utility iso-curve, which bring about the same utility for itself, but likely different utility values for the other agents. Therefore the Developer agent needs to use his knowledge about agent a_1 to approximate the evaluation function of this agent. In other words, the Developer agent is interested in knowing the probability of the acceptance of scenario S_2 considering a hypothetical evaluation function obtained using previous experiences. The translation of the stated probability using the Bayesian approach is:

$$P(h_j|S_t) = \frac{P(h_j)P(S_t|h_j)}{\sum_{k=1}^{m} P(h_k)P(S_t|h_k)} \qquad \text{(Equation 3.3)}$$

where S_t is the land development scenario proposed at time t, h_j is the hypothetical evaluation function that the Developer agent wants to test, $P(h_j)$ is the probability of hypothesis h_j, and $P(S_t|h_j)$ represents the probability that scenario S_t might have been proposed given hypothesis h_j. The details of the selection of this hypothetical function are presented in Section 3.2.4.3.

Learning mechanism

In this study, the Developer agent knows the preferences of the opponent agents, but is unaware of the functions that are used by the agents to evaluate the proposed scenario. The awareness of the Developer agent about the preferences of other agents roots in the nature of the land development application; in the real world it is unlikely that a developer has no information about the perspectives of other stakeholders regarding a land development plan. However, the developer is usually not fully aware of the flexibily of these stakeholders and what they call a satisfactory land development scenario. Therefore, this can be considered as a learning requirement for this type of negotiation where the Developer agent attempts to learn the evaluation functions of the opponent agents. This will enable the Developer agent to make educated guesses for its future proposals. Therefore the Developer agent needs to approximate the evaluation function of the opponents using the information obtained through the previous rounds of negotiation.

In this study, the approach of Hindriks and Tykhonov (2008) is used for such approximation. The basic assumption is that the utility function of each agent can be obtained from Equation 3.1. Moreover as mentioned in Section 3.2.2.2, a fuzzy evaluation function is considered for each agent. The objective of the learning module is to enable the Developer agent to learn the approximate evaluation functions of its opponents. Hindriks and Tykhonov (2008) have introduced three structures for the shape of the hypothetical evaluation function. The first one is *downhill* shape where the evaluation of issue decreases by the increase of the value of the issue, *i.e,* mininimal values are desired. The second function type is *Uphill* shape where the evaluation of issue increases by the increase of the value of the issue, *i.e,* maximal values are desired. With the third function type, called *Triangular* shape, an issue value is considered maximum and evaluations made to the left and right of this value linearly decreases. The three common function types can be further combined to model more complex function types. Figure 3.3 illustrates a more complex evaluation function that can be obtained from the combination of these three function types.

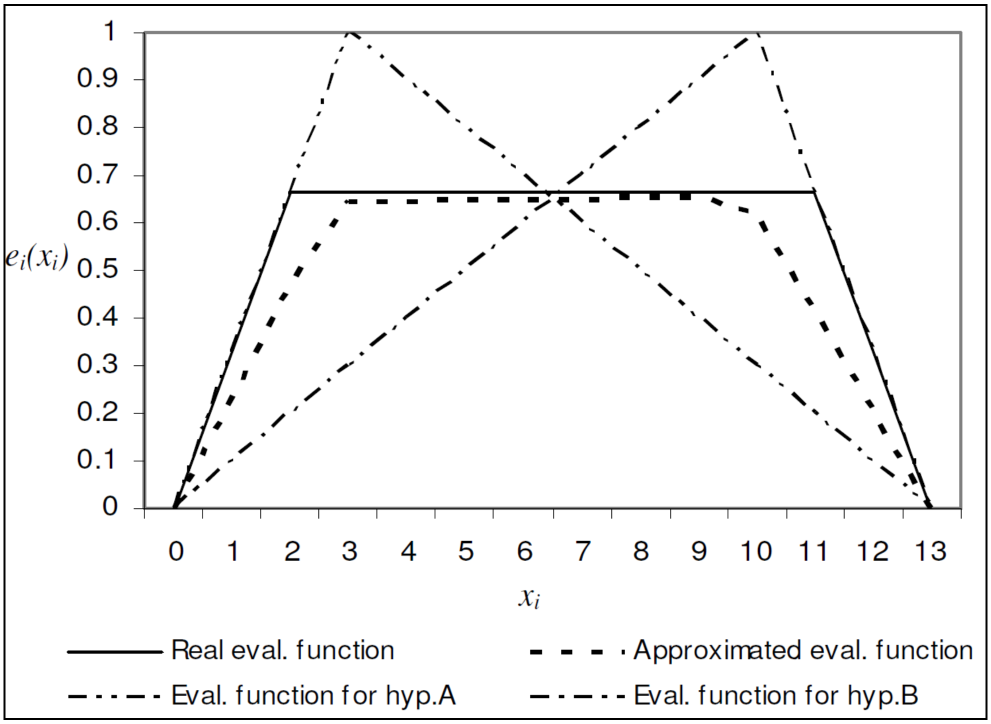


Figure 0.14. Approximation of the opponent agents' evaluation function (Hindriks and Tykhonov, 2008)

Each opponent agent has its own evaluation function that the Developer agent needs to learn. Then, the Developer agent uses these functions to propose a more desirable offer to the other agents, *i.e.*, an offer that brings satisfaction to a greater number of agents. At each round of the negotiation, based on the proposed land development scenario and using the response received from the opponent, the Developer agent calculates the probability of the hypothetical evaluation function using Equation 3.3.

As stated in Section 3.2.4.2, the ultimate goal of the learning module is to compute the $P(h_j|S_t)$, which is the probability of hypothetical evaluation function h_j where S_t is the land development scenario proposed at time *t.* According to Equation 3.3, we have all the values of that equation except for $P(S_t|h_j)$, which is the probability of scenatio S_t, given hypothesis h_j at time *t.* Such probability can be computed using the following formula:

$$P(S_t|h_j) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(u(S_t|h_j)-u'(S_t))^2}{2\sigma^2}} \qquad \text{(Equation 3.4)}$$

where $u(S_t|h_j)$ is the utility of the opponent agent, give the hypothesis h_j and $u'(S_t)$ is the utility calculated by the Developer agent knowing the preferences of the opponent agent. σ is the value that depicts the certainty of the Developer agent about the opponent's negotiation strategy. Obviously by increasing this value the learning speed increases but the value for this parameter should be considered cautiously.

Experiment

According to Xiang and Clarke (2003), land development scenarios can be evaluated according to five characteristics: (1) *alternatives,* which depicts the possible choices of land-use plans, policies, and regulations, (2) *consequences* as the various social, ecological, and economic effects of adopting a certain alternative, (3) *causations* as the causal relationships between alternatives and consequences, (4) *time frames* that describe the time period between adopting the alternative and revealing the consequences, and (5) *geographical footprints* that depicts the effects of the alternative on the geography of an area. In this study, various alternatives of land development scenarios are evaluated. The Developer agent generates these alternatives and proposes them to the other agents. With a focus on the geographical footprints, the agents evaluate an alternative considering the consequences it might have on the study area. This is done using the preferences of the agents and their evaluation functions.

To demonstrate the effectiveness of the Bayesian learning approach, a land development plan was selected based on the Municipal growth management strategy (Rocky View Municipal District, 2009). The area selected for development is highlighted by a circle at the bottom of Figure 3.4. Four main cases were considered as the inputs to the model.

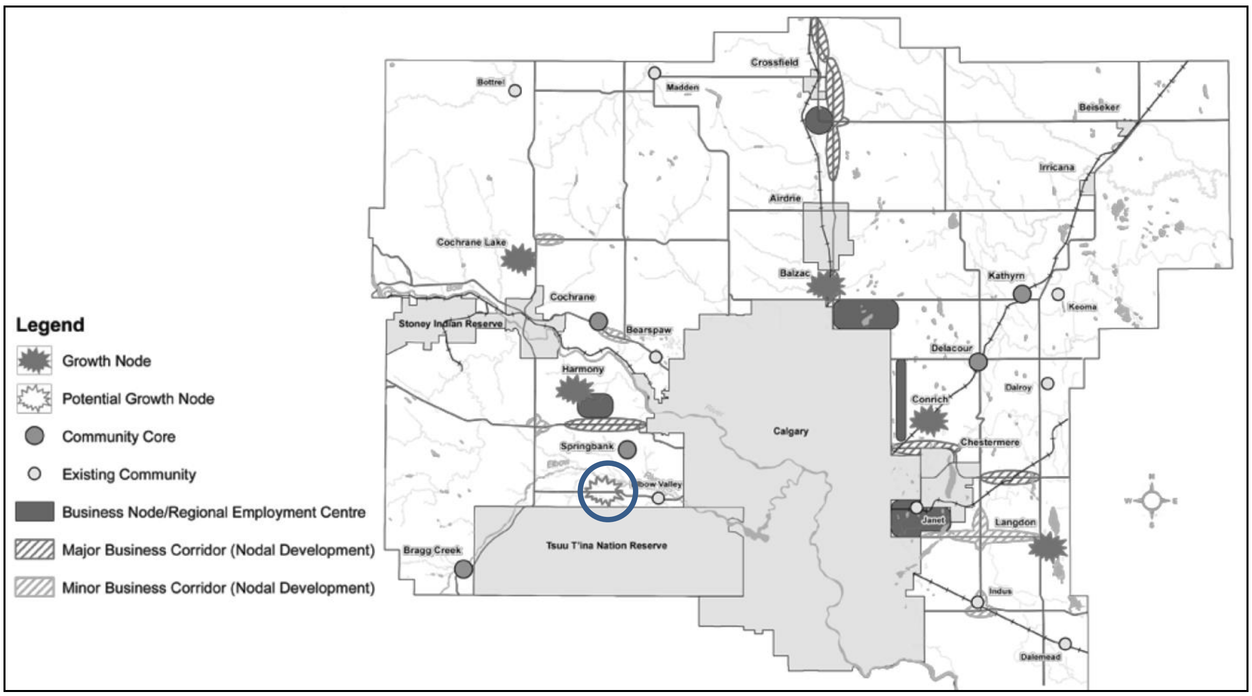


Figure 0.15. Location selected for land development plan (Rocky View Growth management strategy, 2009)

In the first case, the Developer agent adopts an approach based on its own utility only to make the next offer; this agent sorts the geographical locations based on its utility and proposes them in a descending order; we refer to this case as *LocationChange_No-learning* approach, in which the Developer agent does not use the learning module and generates the offers based on the changes in the location of the proposed land development only. In this case if two land developments are located on its utility iso-curve (have the same utility value), the agent selects one randomly. In the second case referred to as *LocationChange_Learning*, the Bayesian learning approach is employed by the Developer agent to make a new offer to the other agents; but still only the changes in the location are considered in the offers.

In the two additional cases, the Developer agent not only has the option of changing the location of the development plan, but he is also able to change its internal configuration by adopting different densities and combinations of land uses. In these cases the developer agent varies the density of the land development plan which in turn changes the portion of each land use type which consequently changes its utility value. These cases were also run with learning and without learning options and are respectively referred to as *ConfigurationChange_Learning* and *ConfigurationChange_No-learning*. Figure 3.5 illustrates the location of the proposed land development within the watershed. This location has been identified as one of the potential growth nodes in the Elbow River watershed, due to its proximity to the city of Calgary and being at the vicinity of two main highways (Rocky View Growth management strategy, 2009).

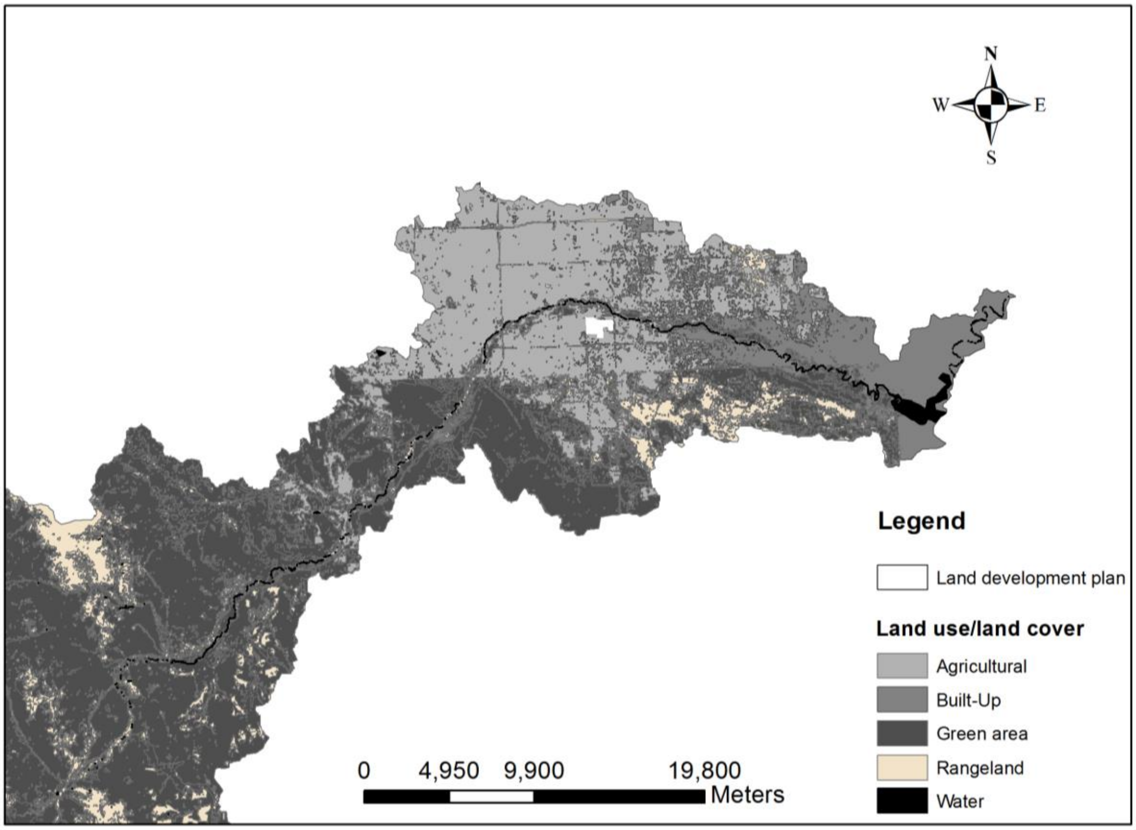


Figure 0.16. The location of the land development within the watershed

Figure 3.6 illustrates the internal configuration of a hypothetical proposed land development, which contains four land uses/land covers, namely residential, recreational, open space, and a waste water management site. The Developer agent can vary the residential density, which affects the amount of land dedicated to other land uses. For the initial plan, a low density was considered to provide more room for negotiation.

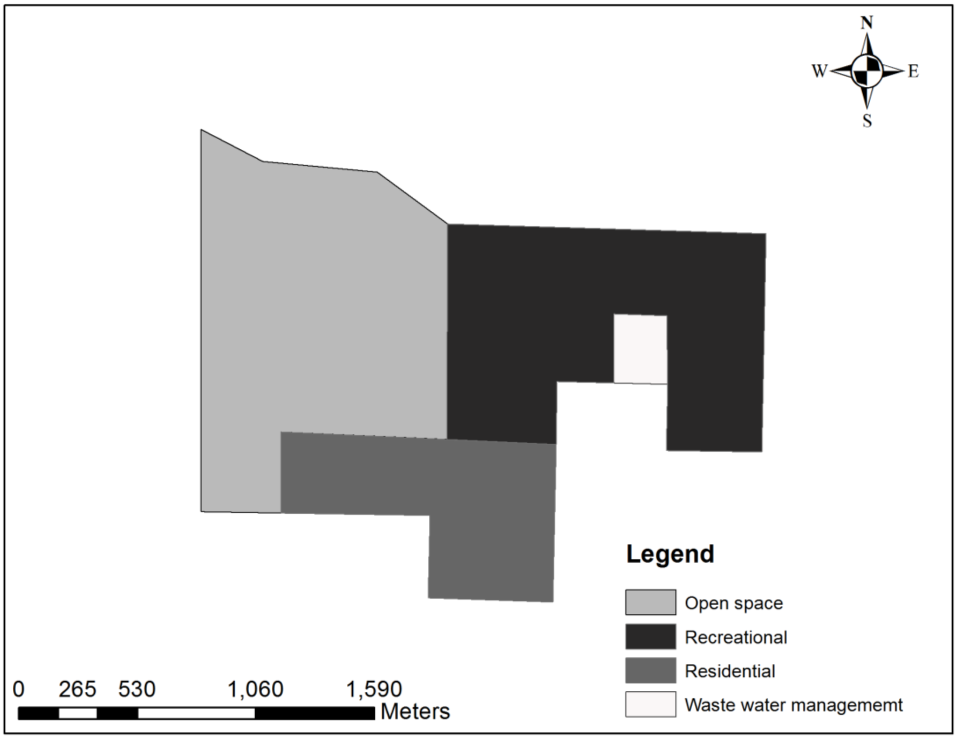


Figure 0.17. Details of the land development plan

Several alternatives were created to be used by the Developer agent based on different densities and different amounts of land dedicated to each land-use type. With the increase in density, more land is dedicated to open space and recreational area and less to the residential area.

A minimum satisfaction of 60% was required for a deal to be accepted by the agents. This value was selected as a reasonable compromise between higher and lower values to capture the dynamics of the negotiation. As expected, tests conducted with higher values resulted in a large number of negotiation rounds to achieve an agreement. Since the aim of the study is to demonstrate the achievement of agreement through learning, the selected threshold does not affect the objective, only the time required to complete the negotiation. Moreover, the users of the system can modify this value prior to the negotiation and examine different scenarios based on different required satisfaction values. A small value of 2% was considered for δ, which corresponds to the interval for the utility iso-curve (Section 3.2.3).

Results

Figure 3.7 illustrates the values obtained for the LocationChange_No-learning case. As it can be seen, it takes 11 rounds to the agents to reach an agreement.

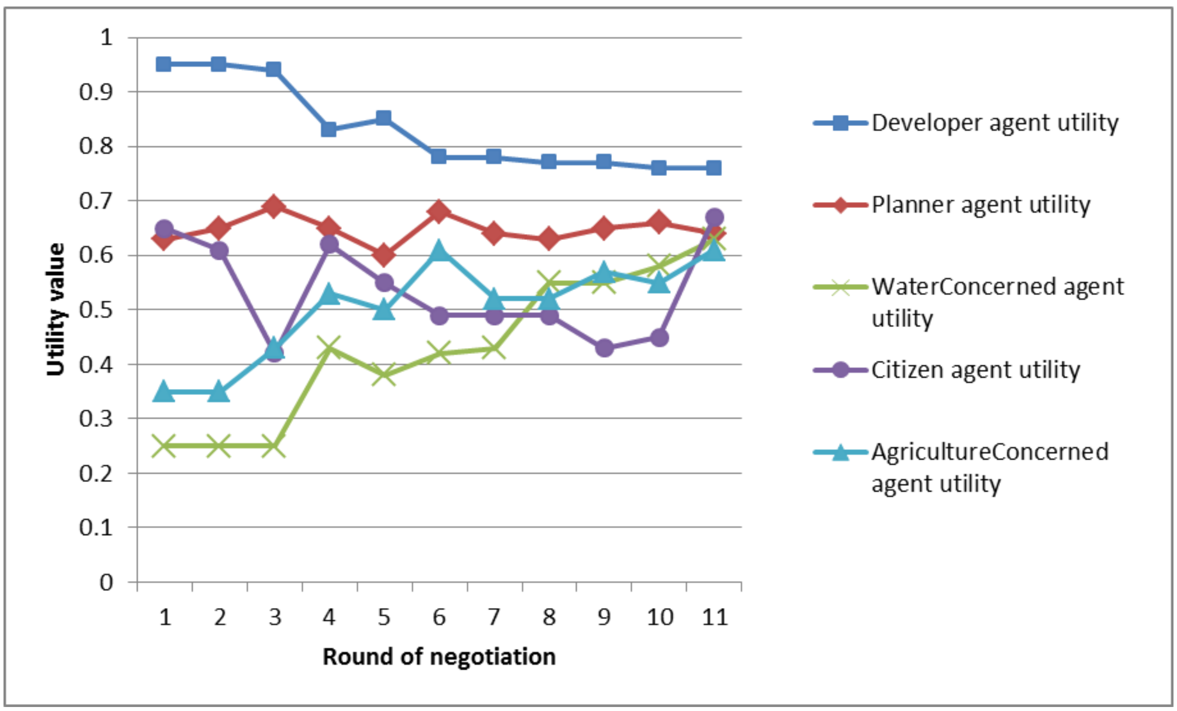


Figure 0.18. Fluctuation of the utility value of each agent in in the LocationChange_No-learning case

The utilities of the Planner and Developer agents change more smoothly compared to the other agents. Moreover, the Planner's utility values are closer to those of the Developer agent compared to the other agents. The WaterConcerned agent's utility values increase smoothly with the changes in the location of the plan. The further the proposed plan is from the sensitive areas considered by this agent, the higher the utility it gains. The same trend is true for the AgricultureConcerned agent, whose utility is highly related to the amount of developed agricultural lands. The Citizen agent considered several factors when evaluating a proposed land development, which causes more fluctuation in its utility values at different locations compared to the WaterConcerned and AgricultureConcerned agents.

Figure 3.8 shows the results for the LocationChange_Learning case. Two concessions were made by the Developer agent in this case. The utilities obtained in rounds 1, 2 and 3 form the Developer agent's first utility iso-curve which does not result in an agreement. Therefore a concession was made by the Developer agent and a new utility iso-curve was generated. A sudden increase in the utility value of the agents occurs after round 3 of the negotiation. After gaining knowledge about the evaluation functions of the agents, the Developer makes an offer that increases the utility value of the agents. This highlights the effectiveness of the learning component in this model. Similar to the no-learning case, increased fluctuation can be observed in the citizen agent's utility compared to the other agents.

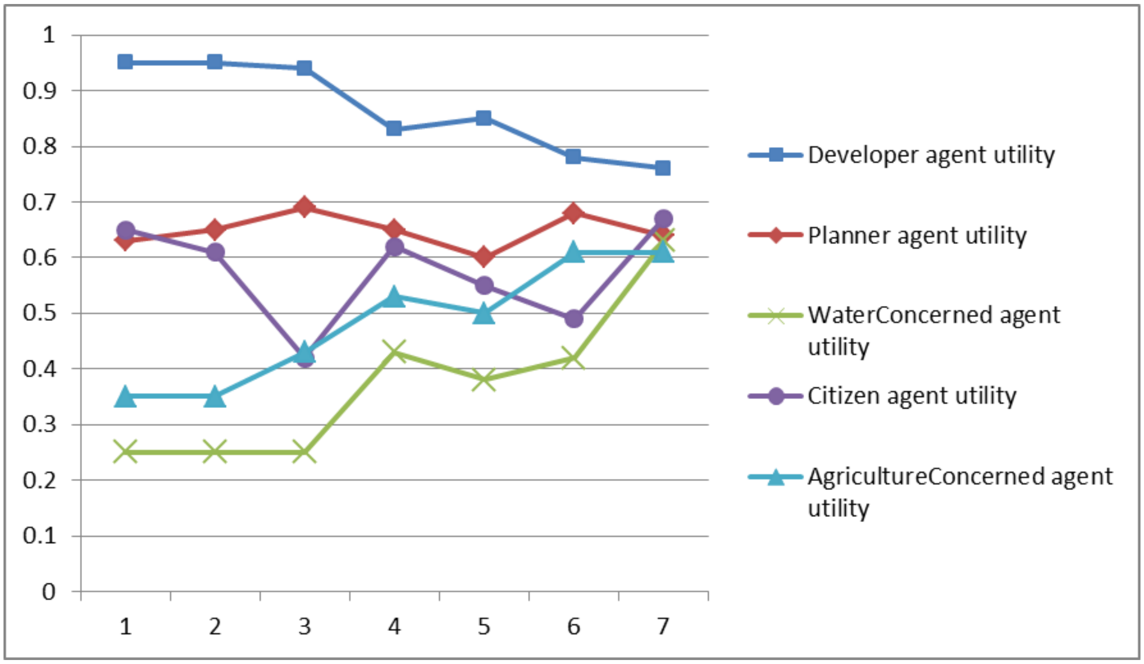


Figure 0.19. Fluctuation of the utility value of each agent in the LocationChange_Learning case

Another concession was made by the Developer agent at round 6 of the negotiation. This means that the third iso-curve of the Developer agent was formed at this stage. An agreement was reached at round 7, while in the no-learning case the agreement was achieved in the 11th round. As it can be seen from Figure 3.8, using the learning approach the agreement is achieved faster and the rate of convergence of the utilities is higher compared to Figure 3.7.

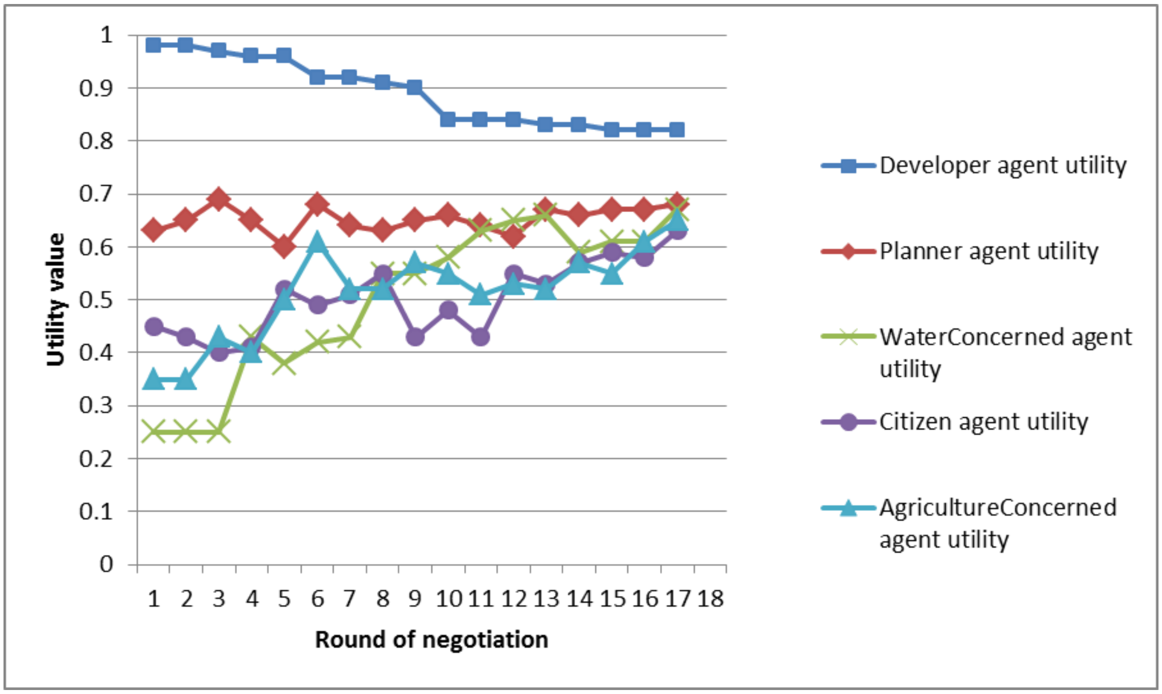


Figure 0.20. Fluctuation of the utility value of each agent in the ConfigurationChange_No-learning case

The results obtained for the ConfigurationChange_No-learning case reveal that more fluctuation exists in the utility functions of the WaterConcerned, Citizen, and AgricultureConcerned agents (Fig. 3.9). This is due to the fact that here location is not the only factor for changing the utility values and therefore the changes are more sudden. However, the Developer agent's utility changes smoothly because of the larger number of available alternatives. Similar to the previous case, the utility values of the Developer agent in rounds 10 to 17 belong to the same iso-curve (or are very close); however since the Developer agent did not use the learning technique, no priority were given to these alternatives and therefore the agreement was achieved at the 17th round.

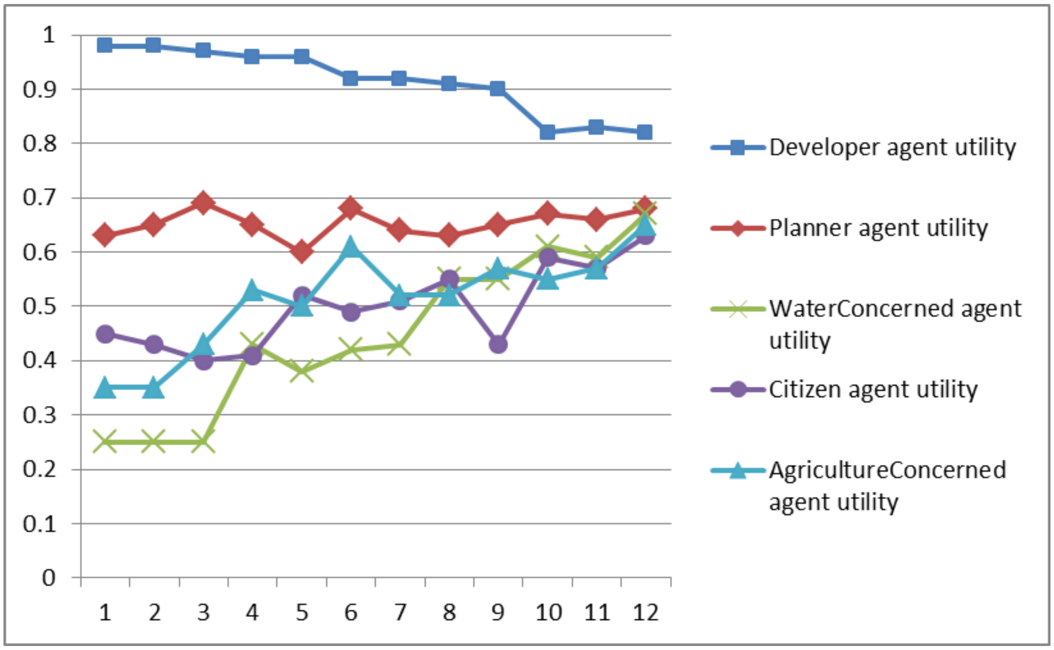


Figure 0.21. Fluctuation of the utility value of each agent in the ConfigurationChange_Learning case

Figure 3.10 displays the values obtained for the ConfigurationChange_Learning case. It can be observed that two concessions were made by the Developer agent; in the third utility iso-curve, the scenarios were selected based on the learning conducted in the previous rounds. The agreement was achieved on the 12th round. Similarly we can see that the convergence of the agents' utility values is faster in this case compared to the no-learning scenario.

Conclusions

Engaging stakeholders in the decision-making process is essential to tackle increasing environmental resource and land sustainability problems (Petrov *et al.*, 2013). Agent-based modeling is a suitable approach to achieve this goal. It allows the simulation of land development scenarios while taking explicitly into account the perspectives of stakeholders at the individual level. Furthermore, the collaborative nature of negotiation in which stakeholders interact to achieve a common goal is enabled through automated agent-based negotiation.

This study was undertaken to examine the impact of incorporating a learning technique to improve the achievement of agreement in agent-based negotiation regarding land development in southern Alberta. Five agents were considered in the negotiation: the Developer agent, the Planner agent, the Citizen agent, the WaterConcerned agent, and the AgricultureConcerned agent. The Developer agent was equipped with Bayesian learning capability to predict the evaluation functions of the opponent agents and propose development alternatives not only based on its own utility, but also considering his opponents' preferences. At each round of the negotiation, the Developer agent considers different shapes for the evaluation functions of the opponent agents and computes the probability of this hypothetical evaluation function given a specific land development scenario. Among the alternatives on the iso-curve of the Developer agent, the one that yields a higher predicted evaluation for the opponents is proposed.

To test the impact of the proposed learning approach on the negotiation, a land development plan was considered based on growth corridors proposed by the local municipality. Two cases were evaluated, both implemented with and without learning capability. In the first case, the Developer agent makes offers by changing the geographical location of the development plan while in the second case the agent changes both the location and the inner combination of land uses in the proposed plan.

The results indicate that the learning module enhances the negotiation and reduces the number of rounds required by the agents to achieve an agreement. This study highlights the significance of learning among the parties by considering the opponents' perspectives in the negotiation over land development. An interesting aspect is the automated generation of alternative scenarios by the computer model, which provides a faster and more systematic search over the space of possible solutions compared to alternatives generated by the stakeholders themselves. In addition, the explicit incorporation of a spatial component in the definition of alternative land development scenarios enables the agents to learn about the geographic footprints of their decisions. The model can be used by decision makers to understand how different land development alternatives impact the satisfaction level of stakeholders and what the outcome of considering or ignoring their viewpoints could be.

Our model can be further improved by allowing the agents to modify their strategies during a negotiation based on the feedback they receive from their opponents. This is an important aspect to consider in attempt to better mimic the negotiation process that happens in the real world; numerous decisions regarding land developments have major flaws due to the inefficiency of negotiation strategies.

Acknowledgements

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Conclusions and Future work

This research aimed at incorporating the perspectives of stakeholders as social actors and facilitating their negotiation process over land development scenarios in the Elbow River watershed considered a CHANS. To achieve this goal, two main challenges needed to be resolved. The main one was to select the appropriate conceptual and methodological approaches to adequately capture the negotiation of stakeholders in the context of CHANS research. A multi-disciplinary framework was proposed which integrates concepts and methods from Complexity theory, Post-normal science and Artificial intelligence.

Due to the complex interactions of stakeholders, the agent-based modeling approach derived from Complexity theory was used to represent them using autonomous goal-oriented agents. The agents were equipped with certain behaviors and properties that govern their interactions. Through these interactions, each agent seeks the accomplishment of its own goals. The complexity of a CHANS which rises from these interactions could therefore be modeled using this bottom-up modeling approach. Other characteristics of complex systems were observed in this study. Feedback exists among the stakeholders in the sense that their future decisions are influenced by the information they receive from each other. Although this study made an assumption of rationality for the agents, human decision making is in nature a complex non-linear process in which complex social and cognitive factors are influential (Dougherty and Thomas, 2012). Moreover the agents of the model which represented the stakeholders can adapt to new situations by learning from the previous experience. The opinions of the agents evolve as result of the learning in the negotiation process.

Post-normal science was included in this framework to provide scientific guidelines for the engagement of stakeholders. Three main ideas that are at the core of Post-normal science were implemented: the involvement of an extended peer community, the rejection of an optimum solution, and the handling of uncertainty. The involvement of an extended peer community requires the employment of tools that facilitate such involvement. Therefore a web-based environment was developed so that anyone who shares a stake or interest in the land development issues in the study area could participate, allowing the inclusion of plural wishes.

Moreover, rather than attempting to find an optimum solution for land development, a solution was sought that was satisfactory at a minimum level to all stakeholders that are involved in the negotiation. Finally, due to the unwillingness of the stakeholders to assign crisp numeric values to their preferences and to take into account the uncertainty associated to such preferences, a fuzzy approach was employed to translate the stakeholders' perspectives into the model.

A requirement for the incorporation of stakeholders' perspectives in the negotiation process is to enable the agents to perform intelligent human-like behaviors. Although the agents are autonomous entities that can interact, they require a certain level of intelligence in order to conduct a complicated process such as negotiation. They need to generate meaningful offers, exchange information, modify their behaviors throughout the negotiation, and learn based on previous experiences. Such intelligence was provided through AI techniques. Due to the long history of AI in incorporating intelligent behaviors in computer models, several techniques were available to equip the agents with features such as learning. Suitable approaches from the literature were examined and Bayesian learning was selected and then modified to fit the negotiation problem in the context of land development. While AI literature focuses on learning the preferences of the opponents, which is suitable for anonymous agents negotiating in an e-market, our interviews depicted that in real-world negotiations over land development scenarios the stakeholders would be happy to share their preferences. However, conflict among stakeholders arises from the fact that the thresholds that they consider for labeling a land development scenario as satisfactory are unknown to the opponents and in fact are also fuzzy in nature. Therefore, fuzzy evaluation functions were developed to represent different preferences of the stakeholders based on the conducted interviews and were included in the model as the evaluation functions of the agents.

This study demonstrates the effect of equipping the agents with two capabilities of increasing sophistication: first with the ability to change their attitudes throughout the negotiation, and second to learn their opponents' negotiation behavior. In the first part of this study (Chapter 2), the agents changed their attitude throughout the negotiation by changing the weights they assigned to different criteria within the interval determined by the obtained fuzzy weights. The results showed that changing weights can facilitate the achievement of agreement; however, the success of the negotiation is limited because the proposer agent does not consider the experiences gained during the previous rounds of negotiation to make succeeding offers. Since an approach was sought in which the agents not only consider their own preferences but also attempt to facilitate a collective satisfaction among agents, a learning component was added to the model. To test the impact of such learning, two different cases were examined; in the first one, the developer agent only changed the location of the land development proposals to produce new alternatives while in the other one, the inner configuration of the development plans was also modified by the agents. A comparison was made with cases in which the agents did not have the learning capability. The results indicate that the inclusion of learning capability allows the agents to yield an agreement within fewer rounds of negotiation.

Thesis contributions

The main contributions of this study can be summarized as follows.

First, the approaches and techniques from three disciplines, namely Complexity theory, Post-normal science and Artificial intelligence were integrated to propose a scientific framework for the modeling of negotiation in CHANS. Agent-based modeling derived from Complexity theory was used to model the interactions of the stakeholders regarding land development scenarios. Post-normal science delivered guidelines for the engagement of stakeholders while AI techniques were used to equip the agents with the required functionalities to mimic human negotiation. Through such integration, our research takes a different path compared to spatial optimization approaches and many AI studies. Optimization approaches mostly use mathematical models to find the best set of values for an objective function and therefore does not take into account the interactions between the involved stakeholders. This study does not employ a pure competitive negotiation approach that only considers the agents' self-interest (Guttman and Maes 1998) to find an optimum solution. In contrast, it employs a semi-competitive approach (Luo *et al.*, 2003), in which the agents search for a solution that satisfies all parties but also maximizes their own utility.

Second, to the best of my knowledge, this study is the first one that explicitly incorporates the spatial component of CHANS in a negotiation problem. In e-commerce negotiation, which is the main focus of numerous agent-based negotiation models, the agents perform simple evaluations of proposed offers. In this study however, the agents evaluate land development scenarios that have spatial characteristics that need to be taken into account. Therefore the agents were equipped with GIS functionalities to perform spatial analyses in order to consider the spatial component in the negotiation.

Third, the web-based environment developed in this study is an example of employing state-of-the-art geo-spatial technologies to incorporate stakeholders' perspectives. While the physical participation of stakeholders is not always feasible, a web-based tool can act as a virtual participatory environment. This is particularly important considering the necessity of involving an extended peer community. Due to the simple design of the developed web interface, it can be used by any interested non-expert stakeholder. Offering simple mapping tools, it provides the stakeholders with information regarding the spatial characteristics of different land development scenarios.

Future work

This study provides a set of valuable tools for the incorporation of stakeholders' perspectives in the negotiation over land development; however a number of improvements could be done.

In this study, the developer agent attempts to learn the evaluation functions of the opponents and therefore proposes alternatives based on this acquired information. Moreover, the agents are able to change their attitudes throughout the negotiation to facilitate the achievement of an agreement. It would be beneficial to incorporate the notion of strategies for the agents (Meyer and Eymann, 2003), which could be modified during the negotiation to obtain the maximum benefit for the stakeholders they represent (Louta *et al.*, 2008). This requires defining different strategies for the agents so that they can switch between them at different steps during the negotiation (Chen and Weiss, 2013). A strategy of negotiation will indicate to an agent the time to make a new offer or insist on the previous offer and ask the opponent to relax its preferences. Such strategies will provide a higher level of intelligence to the agents.

The developer agent is also capable of learning the evaluation functions of its opponents; however it is a good practice to enable the agents to modify their own preferences based on the response they receive from other agents and then evaluate the impact of such modifications on the outcome of the negotiation. This will introduce the notion of *dynamic acceptance conditions* in which the agents dynamically change the conditions under which they accept an offer throughout the negotiation based on acquired information (Baarslag *et al.*, 2013).

Linking the negotiation support system with economical models can also be an interesting avenue for future research. Economic models can be used by the agents to calculate a more precise utility for each land development alternative. The integration of economic models and agent-based modeling has led to the emergence of *Agent-based computational economics* (ACE) (Tesfatsion 2001). The models developed in this domain have been successfully applied in areas such as land markets (Parker and Filatova 2008, Straatman and Marceau 2011), macroeconomics (Heathcote *et al.* 2009), and ecological economics (Heckbert *et al.* 2010). In the context of land management, such economic models focus on the allocation of land as a valuable resource between competitive uses (Parker and Filatova 2008). With an emphasis on land markets as the mechanisms for such allocation (Filatova *et al.* 2009), studies in this area challenge the classical models of urban economics (Alonso 1964) that rely on a top-down construction by incorporating a bottom-up approach such as agent-based modelling (Tesfatsion 2006). They build a laboratory in which economic agents (*e.g.*, traders, financial institutions) interact with other agents representing social and environmental factors (Tesfatsion 2002) to simulate the future state of the system. Such a virtual laboratory can then be employed to examine different scenarios by changing the model parameters. While the integration of economic models and the negotiation support system was out of the scope of this study, it can be considered as an interesting avenue for future work.

Another issue that needs to be considered is the notion of irrationality among the agents and its effects on the results. In this study, the rationality assumption was considered for the agents' behaviors and therefore no room was considered for the possible emotional behaviors of the agents throughout the negotiation. However, stakeholders stated during the interviews that in many cases irrational and emotional actions change the equations in land development negotiations. The system developed in this study has the potential of incorporating emotional behaviors and examining their outcomes. The influence of power imbalance among the stakeholders was not considered and a similar satisfaction threshold was used for all stakeholders despite the fact that this is not the case in real world negotiations. This was done to avoid underestimating the perspective of certain stakeholders and demonstrating that an agreement could be reached in the presence of a similar satisfaction threshold. However, it would be interesting to investigate the impact of an uneven distribution of power among agents on the negotiation results.

Due to the emergent nature of patterns revealed in agent-based models, their validation has always been a challenging task, particularly in cases where the subjectivity of human perspectives is involved. In this study, a verification of the model was conducted by using independent tools such as MATLAB and ArcGIS software package to check that the results are free of errors (Section 2.2.4). Several approaches have been proposed for validating agent-based models including validation using historical data, predictive validation, sensitivity analyses and face validity (Xiang *et al.*, 2005). Face validation is an appropriate technique in this study. A workshop is being organized with the stakeholders so that they can validate that the preferences of the agents in the model are compatible with their own criteria. Moreover they will comment on whether the model yields logical results. Although the simulation outcomes might not exactly reflect the stakeholders' expectations, such results can shed light on the limitations of the work that has been done. It will also be helpful to compare the results of the negotiation conducted by the agents against a real-world negotiation with the stakeholders or with the results obtained from another modeling approach.

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Appendix 1. Questionnaire and interview questions provided to the stakeholders who participated in the study

1. What are the goals of your organization regarding land development and water resource management in the Elbow River watershed?
2. What is your role in that organization?
3. Do you play a role as decision maker?
4. Would you describe the land-use development projects expected in your municipality that will affect the watershed? Please locate them on this map.
5. How do you perceive these developments in terms of their potential in affecting the water resources in the watershed?
6. Do you believe that alternative scenarios of land-use development can be envisioned? Please describe them.
7. In your opinion, what are the factors that should be taken into account when planning a land-use development? Please rank them.
8. In your opinion, what is the role of citizens, government agencies, non-profit organizations, city planners in relation to land-use development and water resource management?
9. Do you believe that the mechanism of making decisions about land-use development and water resource management in the watershed is adequate? Do you have suggestions to improve this mechanism?
10. Do you believe that the perspective of some stakeholder(s) is underestimated or overestimated during the decision making process in the watershed?
11. How flexible is your organization regarding its decisions and what are the negotiable and nonnegotiable aspects of these decisions?

12. What kind of actions do you believe should be taken about land-use development in your community?
13. Have you proposed actions to be taken regarding land-use development as part of your role in your organization?
14. Does your organization use any quantitative measures for evaluating the impact of different land-use development plans?
15. What is your perspective on climate change in southern Alberta?
16. Do you believe that climate change can affect the Elbow River watershed? If yes, how and when?
17. When do you think actions should be taken to deal with climate change?
18. What kind of actions do you believe should be taken about climate change by decision makers globally and regionally?
19. Have you proposed action to be taken about climate change as part of your role in your organization?
20. Do you believe that some areas or types of activities within the watershed should be protected? Which ones and why?
21. Do you believe that some types of activities (land use) within the watershed should not be allowed? Which ones and why?
22. What density of land development do you consider as reasonable in the watershed?
23. Do you believe that there are or should be physical or regulatory constraints to prevent land-use development in the watershed? If yes, which ones?

24. In your opinion, how should the water resources in the watershed be allocated to different users/activities?
25. Are you generally happy with the decision of the decision makers in your community about land-use development and water resource management?
26. Is there anything you would like to change about how decisions are made regarding these issues in your community?
27. How do you perceive the potential increase of population in your area? In the watershed?
28. In your opinion, should a limit to the increase of population be imposed in your community? In the watershed?
29. Should a limit to the use of water be imposed in your community? In the watershed?
30. Considering your role in your community/organization, what do you believe you can do to facilitate water resource management in the watershed?
31. In your opinion, what are the biggest mistakes that have been done in terms of land-use development and water management in the watershed?
32. In your opinion, what are the biggest mistakes that can be done in the near future in terms of land-use development and water management in the watershed?
33. In your opinion, what are the best decisions that have been made in terms of land-use development and water management in the watershed?
34. In your opinion, what are the best decisions that could be made in terms of land-use development and water management in the watershed?
35. How much do you trust a computer model?

36. What do you expect from a computer model that aims at facilitating the interactions and discussion among stakeholders regarding the issues of land-use development, climate change and water resource management?

The questionnaire was sent to the stakeholders prior to the interview to inform them of the content of the interview and allow them some time to prepare. The interviews were conducted as an open discussion through which the stakeholders could freely express their concerns. All the interviews were recorded and analyzed afterward to retrieve the required information for the model, expressed as criteria. After completing this step, the interviewees were contacted by email to confirm that the criteria adequately reflected their perspectives. A brief description of the stakeholders' concerns collected during the interviews is presented below. A generic gender form is used to respect the confidentiality of the stakeholders.

Planner: During the interview, the planner discussed several topics including the growth plans, the required infrastructures, the municipal development plan, and the land development plans under review in the watershed. He described the activities that he was conducting to minimize the adverse impacts of a new land development in the watershed. In response to the degree of which the stakeholders are incorporated in the planning process, the planner stated that several requests have been sent to the stakeholders, particularly the citizens, to attend the open houses and express their opinions regarding the land developments. He expressed some dissatisfaction with the level of interest of citizens in engaging with the planning process. Another concern which was also expressed by the planner and other members of the planning team, including an engineer and an environmentalist, was that some of the guidelines and documents that they need to follow are outdated and do not reflect the current issues in the area; in particular the municipal development plan was mentioned by them. However at the time of the interview, a new municipal development plan was under preparation to tackle this problem. Another issue that was discussed during the interviews was the significance of the political power in land development process and the underestimation of many recommendations by the council.

The planner also discussed the programs that were initiated by the municipality to educate the citizens regarding the issues of the watershed. He emphasized the interest of the municipality to arrange meeting with other stakeholders to solve issues regarding the watershed. The planner expected that a computer model will facilitate the interactions of stakeholders and encourage the participation of citizens in the land development issues.

Citizen: A citizen who was highly concerned about the issues of the watershed was interviewed in this study as a representative of the citizen community. His main concerns included the necessity of preserving wetlands, natural trails, and green areas. This citizens' representative expressed frustration regarding the inefficiency of the planning process and the need for a better supervision of the planners' activities. He expressed his deep concerns regarding the sustainability of the watershed considering the high pressure of development in the area. He also believed that the intensity of developments needed to be controlled by the decision makers. He emphasized the importance of the developers to learn about the concerns of the citizens and consider them in their proposal. He expected that a computer model will be able to encourage alternative forms of development in which the natural environment is preserved.

WaterConcerned stakeholder: A stakeholder was interviewed who represented an institution concerned about water issues in the watershed. During the interviews, he expressed his concerns regarding the quality and quantity of water in the watershed. He explained about the educational programs that were developed by his institution to raise awareness about such issues. One of the main issues depicted by the interviewee was the significance of the preservation of the alluvial aquifer which plays an important role in human habitation and agriculture. Moreover he believed that certain regulations should be implemented to preserve the aquifer and indicated that currently recommendations can only be made by environmentalists for the preservation of the aquifer. He expected from a computer model to help raise awareness regarding the availability and quality of water in the watershed. Moreover he expressed the importance of developing tools for investigating the impacts of land developments on water quality.

AgricultureConcerned stakeholder: This stakeholder represented an organization concerned by the preservation of agricultural lands. During the interview, he described the importance of agricultural lands indicating that some agricultural lands are very fertile and require additional attention. He expressed frustration about the fact that many of the current land developments occur in agricultural areas; however acknowledging the inevitability of such developments he proposed the idea of dividing the agricultural lands in the watershed according to their fertility and assigning values to preserve more important lands. His expectation from the computer model included the development of a computerized economic model to calculate the cost and benefits of different land development scenarios in order to find the best solution.

Appendix 2. System architecture

The system designed in this study links a web interface to an agent-based model (ABM), so that the parameters required to run the ABM are inputted by the users through the web interface; the results of the ABM are also displayed to the users through the web interface.

The first step in using this system is signing in to the system through an encrypted page (Figure A-2.1). After login in, the user is directed to a web page that includes the data and information specific to that user. This provides an exclusive profile for each user of the system. A user can update its preferences or the comparison of the criteria using a designed web page. If such comparison is not completed by the user, the one obtained through the interviews will be used.

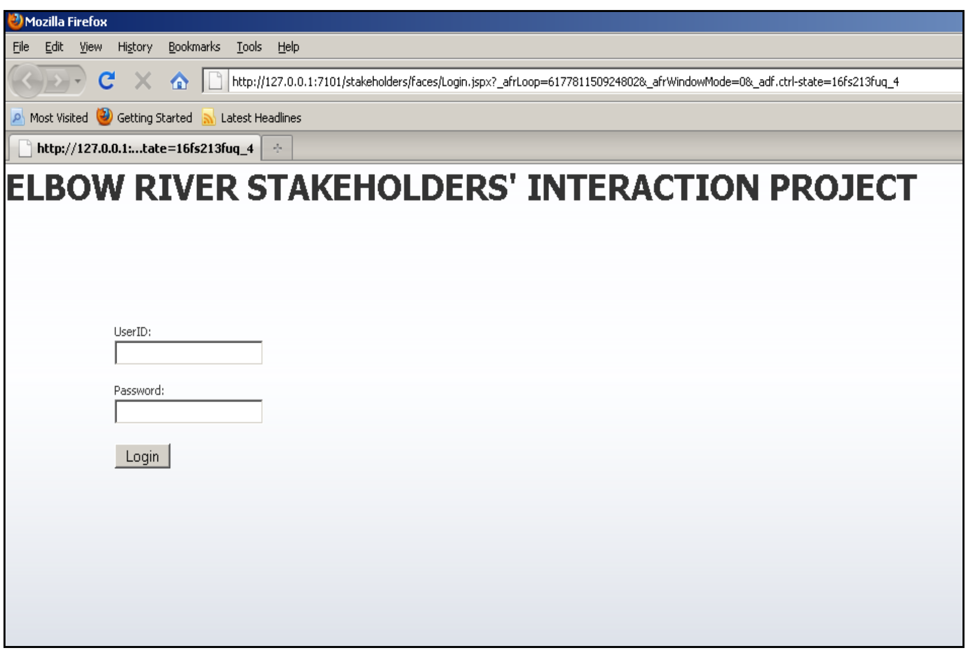


Figure A-2. 1. Login page

Figure A-2.2 shows the criteria comparison tool developed in this study.

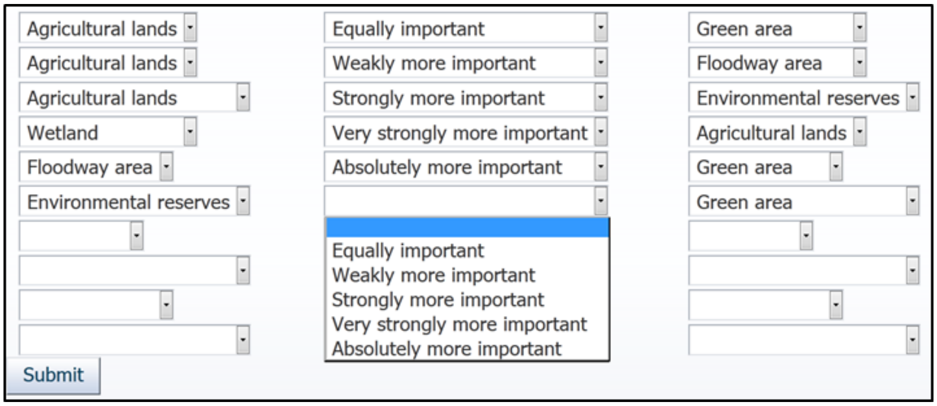


Figure A-2. 2. Web-based tool for the comparison of criteria

Another important web page designed in this study is the one related to the plan proposal. A number of GIS functionalities are provided to the user to draw a land development plan, edit it and submit it to the system. Figure A-2.3 shows the plan proposal page. When the user submits a new plan, it is stored in the database which will become accessible to the agent-based model for the negotiation process.

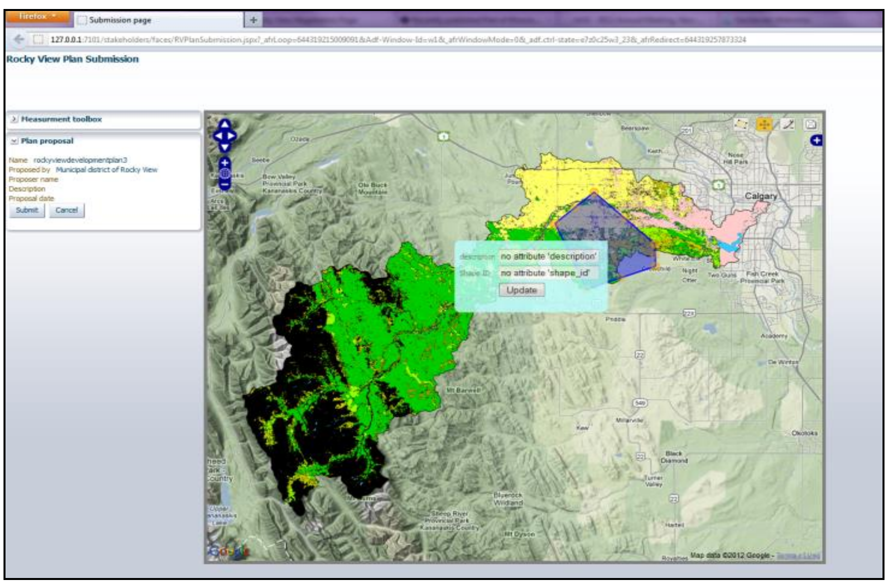


Figure A-2. 3. Plan proposal page

The users can request the system to evaluate a certain proposed plan by comparing it with the current situation of the watershed. Figure A-2.4 illustrates the web page designed for this purpose.

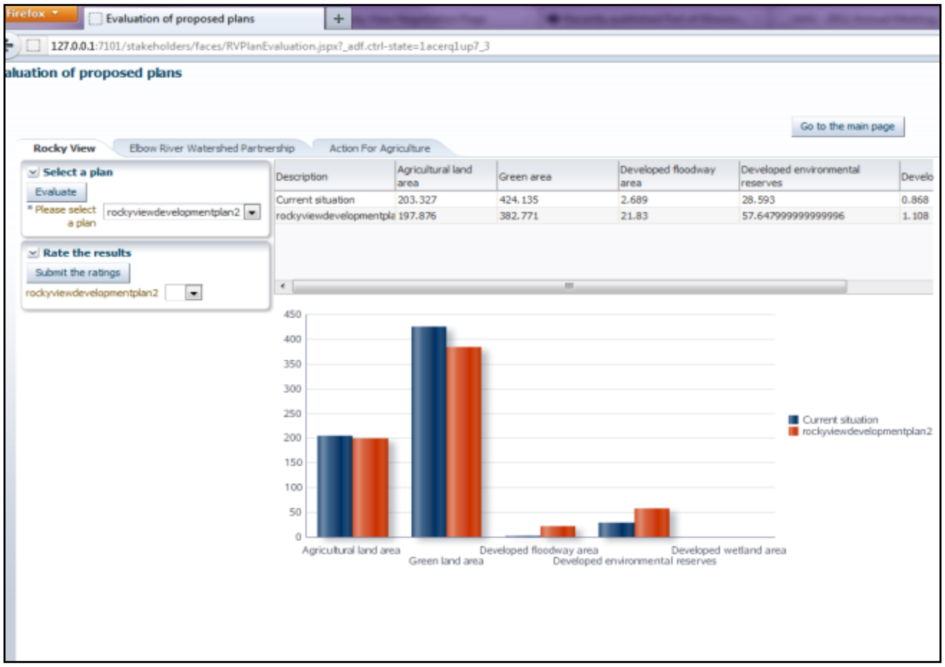


Figure A-2. 4. Land development plan evaluation page

Moreover the results of the negotiation are also outputted through the web interface. After submitting a negotiation request, the users can later sign in to the system in order to view the results of the negotiation.

The design and implementation of this web-based system is based on the architecture illustrated on Figure A-2.5. The following technologies and tools were used in this study for the design of the web interface and its communications with the other components.

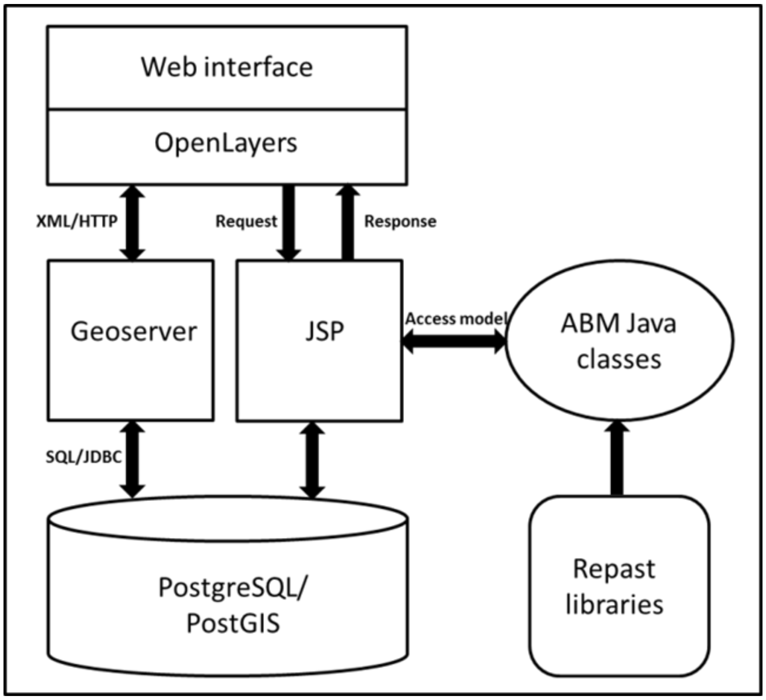


Figure A-2. 5. System Architecture

JDeveloper: JDeveloper was used as an *Integrated Development Environment* (IDE). This IDE is freely supplied by *Oracle Corporation*. The main reason for the selection of JDeveloper as the IDE was its built-in integration with Java technologies that were used in this study.

OpenLayers: OpenLayers is an open source *JavaScript* library for displaying map data in web browsers (Perez, 2012) without any server-side dependencies. In this study, spatial capabilities of the web interface were provided to the user using the OpenLayers functionalities. The GIS tools that are employed by the user to submit a plan or make measurements on the data are provided by the OpenLayers functionalities.

Java server pages (JSP): JSP is a technology for developing web pages that include dynamic content (Bergsten, 2003). Unlike HTML pages which contain static contents, a JSP page can change based on a number of variables such as the selections made by the user. All the server-side processing in this study was conducted using the JSP. The JSP page is responsible for processing the incoming requests and replying back to the client. It communicates with the ABM and sends requests to it and further receives the output of the negotiation and delivers it to the web interface.

GeoServer: GeoServer is a software server written in Java which is used to share, edit and process spatial data. GeoServer is the reference implementation of the Open Geospatial Consortium (OGC) Web Feature Service (WFS) and Web Coverage Service (WCS) standards, as well as a high performance certified compliant Web Map Service (WMS). GeoServer forms a core component of the Geospatial Web (GeoServer web page, 2014). GeoServer reads a wide variety of data formats including *PostGIS*, *Shapefiles*, *ArcSDE*, *Oracle Spatial* and *etc.*

PostGIS: PostGIS is an open source software program that adds support for geographic objects to the PostgreSQL object-relational database. The GIS analyses that are performed by the agents are provided by PostGIS.

Repast Simphony: The main reason for employing Repast Simphony as the agent-based toolkit was its spatial capabilities. In this study the Repast Simphony libraries were inputted to the model as Java libraries to provide the dynamic behavior of agents and the step-wise negotiation process. The agents are developed as Java classes that access the Repast libraries to perform certain actions. These libraries provide the required functionality for the communication of agents in asynchronous time steps. After completing the tasks allocated to the agent-based model, the results are returned to the JSP page which in turn returns the results to the web interface.

The novelty of this design is the integration of agent-based tools with web-based tools. To the best knowledge of the author, this is the first study in which Repast libraries have been employed in a web-based environment. Moreover it has used a wide range of open source products in a seamless architecture. This is one of the few agent-based applications that have used the libraries of Repast instead of using the interface provided by Repast. This allows employing the Repast functionalities without being restricted to its graphical user interface.

Appendix 3. Fuzzy sets

A fuzzy set is any set that allows its members to have different grades of membership (membership function) in the interval [0,1]. A fuzzy set on a classical set X is defined as follows (Wang and Lee, 2010):

$$\tilde{A} = \{(x, \mu_A(x)) \mid x \in X\}$$

The membership function $\mu_A(x)$ quantifies the grade of membership of the elements x to the fundamental set X. An element mapping to the value 0 means that the member is not included in the given set, while a value of 1 indicates a fully included member. Values strictly between 0 and 1 characterize the fuzzy members. Figure A-3.1 illustrates a fuzzy membership function.

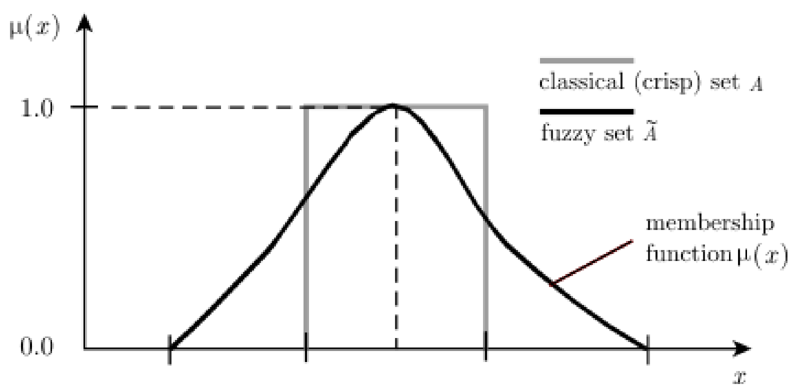


Figure A-3. 1. Fuzzy membership function (Wang and Lee, 2010)

This is in contrast with crisp sets in which a number either belongs to a set or does not belong to it.

$$m_A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases}$$

In this section different membership functions will be reviewed which form the evaluation functions described in section 3.2.2.2.

Type of membership functions

1. Numerical definition (discrete membership functions)

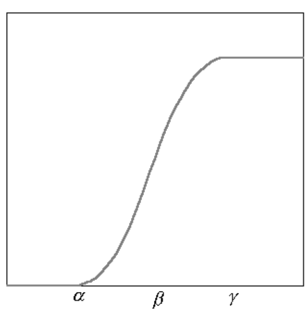
$$A = \sum_{x_i \in X} \mu_A(x_i) / x_i$$

2. Function definition (continuous membership functions)

Including of S function, Z Function, Pi function, Triangular shape, Trapezoid shape, Bell shape.

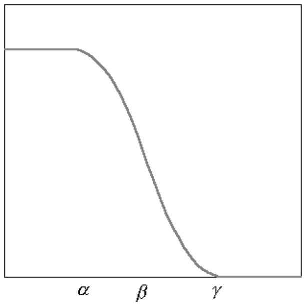
$$A = \int_X \mu_A(x) / x$$

(1) S function: monotonical increasing membership function



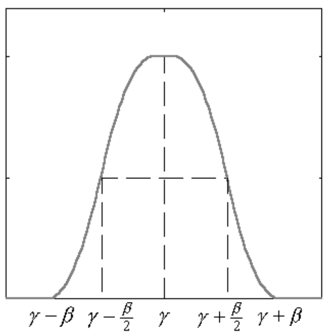
$$S(x;\alpha,\beta,\gamma) = \begin{cases} 0 & for\ x \le \alpha \\ 2(\frac{x-\alpha}{\gamma-\alpha})^2 & for\ \alpha \le x \le \beta \\ 1-2(\frac{x-\alpha}{\gamma-\alpha})^2 & for\ \beta \le x \le \gamma \\ 1 & for\ \gamma \le x \end{cases}$$

(2) Z function: monotonical decreasing membership function



$$Z(x;\alpha,\beta,\gamma)=\begin{cases}1 & for\ x\le\alpha\\ 1-2(\frac{x-\alpha}{\gamma-\alpha})^2 & for\ \alpha\le x\le\beta\\ 2(\frac{x-\alpha}{\gamma-\alpha})^2 & for\ \beta\le x\le\gamma\\ 0 & for\ \gamma\le x\end{cases}$$

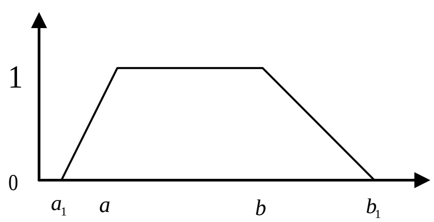
(3) Π function: combine S function and Z function, monotonical increasing and decreasing membership function



$$\Pi(x;\beta,\gamma)=\begin{cases}S(x;\ \gamma-\beta,\ \gamma-\frac{\beta}{2},\ \gamma) & for\ x\le\gamma\\ 1-S(x;\ \gamma,\ \gamma+\frac{\beta}{2},\ \gamma+\beta) & for\ x\ge\gamma\end{cases}$$

Piecewise continuous membership function

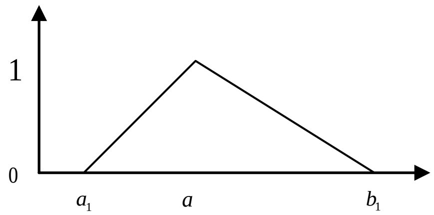
(4) Trapezoidal membership function



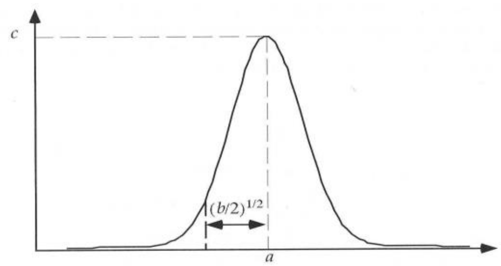
$$\mu_A(x)=\begin{cases}0 & for\ x\le a_1\\ \frac{x-a_1}{a-a_1} & for\ a_1\le x\le a\\ 1 & for\ a\le x\le b\\ \frac{b_1-x}{b_1-b} & for\ b\le x\le b_1\\ 0 & for\ b_1\le x\end{cases}$$

(5) Triangular membership function

$$\mu_A(x)=\begin{cases}0 & for\ x\le a_1\\ \frac{x-a_1}{a-a_1} & for\ a_1\le x\le a\\ \frac{b_1-x}{b_1-a} & for\ a\le x\le b_1\end{cases}$$



(6) Bell-shaped membership function



$$A(x) = c\mathrm{e}^{-\frac{(x-a)^2}{b}}$$

The set- theoretic operations on fuzzy sets are listed below (Pedrycz and Gomide, 1998).

Subset: $A \subseteq B \Leftrightarrow \mu_A \leq \mu_B$

Complement: $\overline{A} = X - A \Leftrightarrow \mu_{\overline{A}}(x) = 1 - \mu_A(x)$

Union: $C = A \cup B \Leftrightarrow \mu_c(x) = \max(\mu_A(x), \mu_B(x)) = \mu_A(x) \vee \mu_B(x)$

Intersection: $C = A \cap B \Leftrightarrow \mu_c(x) = \min(\mu_A(x), \mu_B(x)) = \mu_A(x) \wedge \mu_B(x)$

The arithmetic operations used in this study are listed below. Such operations on fuzzy numbers $\tilde{A} = (l_1, m_1, r_1)$ and $\tilde{B} = (l_2, m_2, r_2)$ are as follows (Pedrycz and Gomide, 1998):

(1) Addition of two fuzzy numbers

$$(l_1, m_1, r_1) \oplus (l_2, m_2, r_2) = (l_1 + l_2, m_1 + m_2, r_1 + r_2)$$

(2) Subtraction of two fuzzy numbers

$$(l_1, m_1, r_1) \Theta (l_2, m_2, r_2) = (l_1 - r_2, m_1 - m_2, r_1 - l_2)$$

(3) Multiplication of two fuzzy numbers

$$(l_1, m_1, r_1) \otimes (l_2, m_2, r_2) \cong (l_1 l_2, m_1 m_2, r_1 r_2)$$

(4) Division of two fuzzy numbers

$$(l_1, m_1, r_1) \varnothing (l_2, m_2, r_2) \cong (l_1 / r_2, m_1 / m_2, r_1 / l_2)$$