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Multi-Agent Systems for Urban Planning and Decision-Making: A Review of the State-of-the-art Methods

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Abstract: Urban planning and decision-making processes can be improved by implementations of computer-based simulations, one of them is by simulating real-world objects as agents in computer systems, widely known as the Multi-Agent Systems (MAS). MAS is a collection of various methods and approaches. Currently, there is no general overview of how this technique is being implemented in the field of urban planning. This study reviews and evaluates the literature about the implementation of MAS to help urban planners and decision-makers to decide which method is the most suitable to solve the decision-making problem at hand.

Key words: Agents, planning, decision, system, hand, decide

INTRODUCTION

One of the streams of research about the implementations of computer systems to improve urban planning and decision-making processes is the simulation of dynamic changes in various aspects of planning and decision-making such as land use, demography and transportation. The early focus of this stream of research was on land-use modelling where different methods developed from various scientific communities resulted with models to simulate processes or patterns of land use change (Castella and Verburg, 2007). Another type of this implementation of computer systems are in form of Geo-simulation which simulate changes on the geographic characteristic in the future, particularly in urban environments (Moulin *et al*., 2004), emerged as the most common early implementations of Multi-Agent System (MAS) in planning and decision-making.

The term of an “Agent” in computer science defined as “a computer system, situated in some environment, that is capable of flexible autonomous action in order to meet its design objectives” (Jennings *et al*., 1998). This autonomous action performed by agents in a way is observable in the field of urban planning and decision-making where multiple entities are making their actions and decisions autonomously to fulfil their objectives. In an agent-based modelling environment, urban planning entities such as landowners, the government, business owners are represented in a digital form as software agents. Those agents can make their own decision based on pre-determined parameters or interaction rules between agents.

The digital representations of urban planning entities, each with a wide range of capabilities, offered resulted in the increased attractiveness of MAS as tools to reproduce and analyse diverse social systems, especially its capability to autonomously making decisions in planning processes. MAS-based simulations have been applied in various aspects of urban planning and decision making (Nakajima *et al*., 2010) and also lead to various Planning Support Systems (PSS) development in planning practices (Kamps and Tannier, 2009). Previous implementations of multi-agent systems in planning and decision making seldom mentioned in what planning and decision-making context the computer model should be utilized. Therefore, this study explores previous implementations of MAS to make an overview about how MAS can be utilized in planning and decision-making context.

Based on their objectives, design objectives and the relationship among agents and their environment, two types of MAS are defined which are the behaviour-modelling MAS and the interaction-modelling MAS. A behaviour-modelling MAS is the type of MAS where the main objective of the modelling is to simulate real-world object’s behaviour when facing changes in their environment while the interaction-modelling MAS’s main objective is to simulate the interaction between real-world objects as discussed in the next studies of this study.

BEHAVIOUR-MODELLING MULTI-AGENT SYSTEMS

The first type of MAS for planning and decision-making is the behaviour-modelling MAS which consists

Table 1: Examples of behaviour-modelling MAS

Example	Input	Method/Component	Output
CA-based land use change modelling (Barredo *et al.*, 2003)	Environmental characteristic Spatial characteristic of the city Planning policies Individual preferences	Cell definition Neighbourhood effects Transitional rules Land use demand	Simulation of present land use change dynamics Future land use change prediction Accuracy assessment Simulation of present land use change dynamics
Logistic regression land use modelling (Fang *et al.*, 2005)	Historical land use maps	Logistic regression Land use Evolution and impact Assessment Model (LEAM) Spatial Modelling Environment (SME)	Future land use change prediction Accuracy assessment
CA-based traffic simulation (Tlig and Bhouri, 2011)	User commands Sensors Vehicle status	Controller Behaviour parameter Behaviour rules	Agent's driving behaviour on the designated road section
Urban environment (Moulin *et al.*, 2004)	Activity areas Terrain data (drainage, slope, soil type, etc.) Path data Agents grouping by age	Agent's navigation, perception and behaviour	Simulated movement of agents Computer support for walking path design
Traffic flow simulation (Angulo *et al.*, 2011)	The volume of vehicles Road segment capacity Driving directions Vehicle parameters Traffic lights timing	O-D data simulation Clustering Timing optimization	Average speed of vehicles Average network travel time Road segment Level of Service (LoS)
Urban traffic flow (Manley and Cheng, 2018)	Road network Traffic flow	Spatial knowledge Route choice	Traffic flow changes The most common route
Land use change modelling (Dragicevic and Hatch, 2017)	Maps of land use Change criteria Agents' hierarchy	Logic Scoring Preference (LSP) Criteria tree Aggregation structure	Land use change scenarios Building construction scenarios

of methods that have the main objective to predict what actions of agents are as a reaction to changes in their environment. Behaviour-modelling methods have a common fundamental characteristic which is they are based on predetermined rules of relationship between agents and their environment not between agents. In some cases of this MAS, agents not only to receive inputs but also have an ability modify their environment (O'Sullivan, 2008).

Based on the general schematic of decision-modelling MAS proposed by Wooldridge (2009), the main objective of this type of MAS is to simulate decision-making process by developing virtual agents that can mimic the behaviour of real-world objects behaviour when making decisions or changing their states. The main assumption of this method is real-world objects made their decisions or change their state based on their perception of the environment and then made an action based on their preferences and objectives and adjusting their preferences based on other decision maker's behaviour. The most common type of behaviour-modelling MAS is the ruled-based ones where agents made their decisions based on a set of pre-determined rules. The most important factor when developing rule-based MAS is a realistic representation of the agent's behaviours with respect to planning and decision-making processes. The potential advantage of rule-based MAS is that the more empirical model is the better it helps planners and decision makers to understand the process (Table 1).

The most popular method of rule-based MAS is Cellular Automata (CA) for land use change modelling (Batty *et al.*, 1999; Ferber, 1999; Berger, 2001; Ligtenberg *et al.*, 2001; Barredo *et al.*, 2003) where study area was divided into cells, thus, each single cell was identified as agent. In a rule-based cellular automata, interaction rules are defined and then, complex interactions between agents and their environment are simulated. As the result, new land use pattern emerged following those interaction rules. The newly emerged land use pattern then compared to previous land use maps to see how good the model can simulate real-world dynamics. Rule-based land use change modelling can also use logistic regression method (Fang *et al.*, 2005) to empirically modelling and analysing land use and land use change. An example of a rule-based MAS can be found in Berger (2001) that simulates land use change in an urban area. In this study, agents are defined as the cells within the study area and inputs of the model are spatial properties of the study area which determined the decision of agents to change into another type of land use or stay as it is. By using two types of CA Models, Economic and Hydrologic Model, the system produced predictions about the behaviour of agents/cell and spatial dynamics of the study area. Another potential application of rule-based MAS is in traffic modelling (Mckenney and White, 2013; Shen and Jin, 2012; Tlig and Bhouri, 2011), a research field which is often related to spatial planning. Traffic is one of the most complex systems in modern society because vehicular traffic includes various aspects:

route selection and driving behaviour (Nakajima *et al*., 2010). Road traffic in an urban environment can be considered as a complex system, resulting from movement of vehicles in the road network with limited capacity. Agent-based vehicle movement is an ideal method to simulate traffic flow by using microscopic traffic simulator. Although, CA-based traffic flow using agents can give useful predictions about traffic dynamics, it has been recognized that driving behaviour simulations with sophisticated agents are also beneficial. Summary and example of implementation of behaviour-modelling MAS can be seen in Table 1.

INTERACTION-MODELLING MAS

Although, behaviour-modelling MAS may provide decision makers with a good prediction about spatial dynamics, there are some drawbacks if decision-making process were fully simulated in a computer system. First, there is a widely known problem in spatial planning practices that planners have doubts towards computer support in decision-making. Thus, planners and other actors involved in the spatial planning are still distrustful or even held an antagonistic point of view toward decisions made by computer models (Harris, 1999). Second, behaviour-modelling MAS required some controls previously fully held by decision-makers to be delegated to a computer system, decision-makers may have concerns about the degree of control they have especially with task delegation to agents (Saarloos, 2006). Third, stakeholders are usually contacted and involved only during data collection phase, a left out during analysis and conclusion stage of researches related to MAS. Transfer of knowledge and result of the research usually took place between academic researchers and decision makers. This is a severe drawback of MAS because the perception of environment, preferences, assumptions and modelling objectives are components of MAS which can be significantly improved if stakeholders involved more actively in the development, testing and use of the model (Becu *et al*., 2008). Although, rule-based MAS can simulate dynamic features with relatively good accuracy, these models fail to address complex changes produced by different behaviour of agents (Zhang *et al*., 2010).

To overcome the drawbacks of behaviour-modelling MAS, researchers have developed another type of MAS which is the interaction-modelling MAS. The main purpose of this type of MAS is to build process model of multi-actor decision making (Parker *et al*., 2003; Ligtenberg *et al*., 2004; Katoshevski-Cavari *et al*., 2010; Zhang *et al*., 2010). The main goal of this type of MAS is to simulate decision-making process to land use allocation by providing a system in which decision makers can explore the implications of their decisions to their environment (Becu *et al*., 2003). The main challenge of this approach is that capturing such complex matters as human decision making may become over-ambitious and those model outcomes often barely reflect reality (Bakker and Doorn, 2009).

Interaction-modelling MAS is where system architecture is developed to provide a realistic representation of the agent's motives, behaviours and interaction with other agents during planning and decision-making processes. In interaction-modelling MAS, the main goal of the system is not to simulate behaviour or decisions made by agents as the output of MAS but rather to use agents 'decisions as an input for the model. Developing interaction-MAS is very challenging because the aim to capture such complex matters as human decision making often turns out to be over-ambitious and those model outcomes often barely reflect reality (Bakker and Doorn, 2009). Translating spatial theories into a complex system to simulate spatial dynamics is rather easy, compare to modelling communication and interaction between actors involved in spatial planning and their conceptual and practical implementations. However, in spatial planning, we need to engage human agents in spatial planning who are generally land users, owners and institutions that all play a certain role in the land use decision-making process.

The main objective of interaction-modelling MAS is to learn properties of interaction between agents (Ferber 1999; Saarloos, 2006). In urban planning and decision-making practices, it is common that agents already have their decisions about their actions in the future. i.e., landowners already have certain or at least give some thoughts about what they will do with their properties. Therefore, it is important to simulate agent's behaviour in changing their decisions if they know what other agent's decisions are and engage in exchange offers. In interaction-based MAS, we can define agents not only as software entities but also as real human actors whose actions and decisions will influence decision-making results.

Similar to behaviour-modelling MAS, interaction-modelling MAS also first developed to simulate spatial dynamics by modelling agent's behaviour and actions as their response to the environment. From previous researchers, there are different types of applications of interaction-based MAS in spatial planning. The first example is in scenario generation (Robert, 2005; Stevanovic *et al*., 2008; Bakker and Doorn, 2009; Campo *et al*., 2010) where MAS is developed to help stakeholders to define possible scenarios in spatial

Table 2: Examples of interaction-based MAS

Examples of application	Input	Model component	Output
Scenario generation and Evaluation (Campo *et al*., 2010)	Agents classification Problem identification	Role-playing game UML-based scenario development Computer simulation	Collective learning Tools to improve discussion and negotiation process
Land allocation (Barnaud *et al*., 2013)	Stakeholders goals Stakeholders roles Plantation system	Internal reasoning of agents Stakeholders negotiation	Stakeholders movement Plantation patterns
Adaptive behaviour analysis (Janssen *et al*., 2011)	Location decisions Development procedures Development Initiatives	Influence structure and factors Classification of interaction Choice modelling	Location preferences Agent's adaptive behaviour
Multi-actor Land use allocation (Zhang *et al*., 2010)	Existing land use map Agents classification (government, residents, etc.) Driving forces of urban expansion	Land use development probability of cell Location utility of cell Variables influencing agent's decision behaviour Agent's decision behaviours	Prediction of urban expansion
Location selection (Arentze and Timmermans, 2003)	Zoning plan Agents types and strengths	Site selection procedure Agent's site preferences Agent's strategies	Location decision Agents clustering Agent's outcomes and gains
Residential behaviour (Benenson, 1998)	City's housing infrastructure Agents representing free-moving residents	Agent's economic properties Agents' cultural properties Migration trade-off	Evolution of a city based on population type (economic or cultural) Cultural pattern and identity
Migration pattern (Fu and Hao, 2018)	Migration data Social network	Social network mapping Space optimization	Migration pattern interdependence

planning. By evaluating each scenario through interaction between stakeholders, they can decide which scenario is the most desirable, thus, implemented in spatial planning.

The second example of interaction-based MAS implementations are in land allocation (Purnomo and Guizol, 2006; Lagabrielle *et al*., 2010; Barnaud *et al*., 2013) where MAS provides a framework which allows analysis of stakeholders interactions and decision-making processes. Because each stakeholder has a specific communication capacity, behaviour and rationales, their specific actions will also emerge. By using stakeholder's characteristic and action pattern, we can use a computer system to simulate a dynamic model of stakeholder's interaction. Previous research related to interaction-modelling MAS shown that this approach is very useful to develop participatory land allocations or even land-use simulations. The advantage of interaction-modelling MAS compared to other type MAS is particularly shown in a conflict situation where a gradual and sequential participatory modelling approach can be implemented to mimic the real-world process of the public decision-making process. By simulating those processes into a multi-agent system, stakeholders have more opportunity to interact with other stakeholders. Examples of interaction-based MAS can be seen in Table 2 which varies from generating scenarios to selecting available alternatives by simulating the real-world interaction between human decision makers inside computer systems.

CONCLUSION

In this study, previous implementations of Multi-Agent Systems (MAS) are examined which resulted in two general types of MAS. The First type of MAS is behaviour-modelling methods which translate agent's behaviour in the real world into a computer system. In this type of MAS, agents are interacting with their environment when making the decision. Thus, changes in their environment will also produce a different agent's behaviour. The Second type of MAS is interaction-modelling methods where agents make their decision based on their interactions with other agents. Behaviour-modelling methods offer a wide array of implementations where a real-world planning and decision-making requires a simulation of agent's behaviour. However, this type of MAS focused more on the interaction between agents and their environment, such as in land use change and traffic modelling. On the other hand, interaction-modelling MAS focused on the interaction between agents.

When a planner or a decision maker selects which type of MAS should be implemented to solve a particular issue, there are two considerations that should be taken into account. Firstly, how decisions are made, whether based on agent's interactions with their environment or based their interactions one to another. The former situation is more appropriate to be solved by behaviour-modelling MAS while the latter is by interaction-modelling MAS. Secondly, how agent's environment influences the decision-making process which leads to the specific method that available within both types of MAS.

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