



University of East London Institutional Repository: <http://roar.uel.ac.uk>

This paper is made available online in accordance with publisher policies. Please scroll down to view the document itself. Please refer to the repository record for this item and our policy information available from the repository home page for further information.

To see the final version of this paper please visit the publisher's website. Access to the published version may require a subscription.

Author(s): Li, Yang. Brimicombe, Allan. J., Chao, Li.

Article Title: Agent-based services for the validation and calibration of multi-agent models

Year of publication: 2008

Citation: Li, Y. Brimicombe, A.J., Chao, L. (2008) 'Agent-based services for the validation and calibration of multi-agent models' Computers, Environment and Urban Systems, 32 (6) 464-473

Link to published version:

<http://dx.doi.org/10.1016/j.compenvurbsys.2008.09.002>

DOI: 10.1016/j.compenvurbsys.2008.09.002

Publisher statement:

<http://www.elsevier.com/wps/find/authorsview.authors/authorsrights>

Information on how to cite items within roar@uel:

<http://www.uel.ac.uk/roar/openaccess.htm#Citing>

Agent-Based Services for the Validation and Calibration of Multi-Agent Models

Yang Li, Allan Brimicombe, Chao Li

Abstract

Agent-based modelling in the form of multi-agent models has been increasingly applied to the simulation of spatial phenomena *in silico*. Validation and calibration are recurrent problems. The complexity of these models with large numbers of parameters can make validation procedures intractable. In this paper, the novel concept of using agent-based technologies to create services that assist in the validation and calibration of multi-agent models is developed. Such agent-based services offer an efficient solution where large numbers of model runs need to be carried out. In this paper, the agent-based services are collaborative sets of agents that perform calibration and sensitivity analysis as a key task in model validation.. In a case study, the prototype agent-based validation services are implemented for a multi-agent wayfinding model as a means of proof-of-concept. The case study demonstrates how agent-based services can be deployed for testing the robustness of emergent patterns through sensitivity analyses and used for model calibration.

Keywords: multi-agent models, verification, validation, sensitivity analysis, calibration, agent-based services, wayfinding, location-based services.

1. Introduction

Agent-based modelling has been increasingly applied to the simulation of spatial phenomena *in silico*. In a spatial simulation using multi-agent models, agents have tended to be defined as spatial objects to computationally represent the behaviour of individuals in order to study emergent patterns arising from micro-level interactions (e.g. Batty *et al.* 2003a, 2003b). More recently, agents have been used to represent spatial processes as the modelling primitives in order to focus on process information in dynamic models (Reitsma & Albrecht, 2005). However, a recurrent problem in multi-agent modelling (and numerical simulation models in general) is the evaluation and

assessment of outcomes (Amblard *et al.*, 2005; Batty & Torrens, 2005; Manson, 2007; Portius *et al.* 2007). Thus a novel approach to using agent-based technologies, investigated here, is to harness the intelligence and network mobility of agents to create tools that offer services for the validation and calibration of multi-agent models. We refer to such services as *agent-based services*. A typical agent-based service for spatial simulation might include quality analyses of both data and models (Li Y., 2006). In this paper we specifically investigate agent-based services for sensitivity analysis and calibration of multi-agent models as an integral part of the validation process. In order to develop an interoperable and distributed system, multi-agent technology is deployed as a collection of collaborating agents that can be shared as services across a network. This paper discusses the need for such agent-based services in relation to the validation of multi-agent models. It goes on to provide a proof-of-concept by using prototype agent-based services to assist in the validation of a multi-agent wayfinding model.

The paper is organised as follows: having presented the objective of the study in the Introduction, Section 2 proceeds with an overview of the concept and application of multi-agent based models in GIScience. Section 3 then discusses the necessity for the validation for multi-agent based models. Section 4 introduces a new approach to validation and calibration using agent-based services. Section 5 presents a case study of using such agent-based services for a multi-agent wayfinding model and Section 6 draws the conclusions.

2. Multi-agent modelling

Various definitions have been given for agents depending on the research area in which they are being applied and which features of agents are being emphasised (Franklin & Graesser, 1997). Whilst there is an on-going debate over the definition of an agent across a number of disciplines (O'Sullivan, 2008), an agent (i.e. a software agent) can be generally viewed as an autonomous, problem-solving, encapsulated entity in a dynamic and open environment (Wooldridge, 1997; Jennings, 2000).

The initial development of remote multi-agent systems comes out of classical artificial intelligence and object-oriented programming (Adler & Cottman, 1989). Remote agents are those which can be accessed across a network as

distributed components (also see details in Section 4). A multi-agent system not only includes a number of agents in an environment but also allows intensive interactions between agents (Parker *et al.*, 2002). This paper adopts and particularly focuses on this concept of a multi-agent system. A multi-agent system can include a model, or several models, or models coupled with agents which provide services in managing information and processes. Key features of agents are their ability to sense and respond to their environment (reactivity) and to communicate with other agents. Other features that provide agents with added intelligence include: autonomicity, pro-activity, adaptivity, social ability, collaboration, cloning, network mobility and ontology (Woolridge & Jennings, 1995).

Within geosimulation (Benenson & Torrens, 2004; Albrecht, 2005), the most common implementation of multi-agent models is for the agents to act as objects within a spatial framework. Agents are used to represent collectives of spatial individuals such as households, roads and land parcels. Simulation models can then be developed as an attempt to understand the aggregate behaviour or emergent patterns arising from the micro-behaviour of individuals which can communicate, sense their environment and interact (Ferber, 2005). When spatial dynamics are embedded in the rules of agents or in the dynamic extensions of agents, the operation of processes can be simulated, stored and queried. Thus, for example in pedestrian modelling (Batty *et al.*, 2003a), agents can simulate the behaviours of individual persons to link uncoordinated actions at the micro level with emergence of more global structures at the macro level. More recently, agents have been used to represent processes in a model to gain new insights into how spatial phenomena operate (Reitsma & Albrecht, 2005).

In integrating with GIS software, agents can be created to represent features that are points, lines, polygons or cells. These agents may be dynamic in their state (i.e. with changing attributes) or space (i.e. changing their location), and may trigger changes in the state or location of other agents. In simulations, they are implemented as discrete events and have the ability of Lagrangian motion. Attempts have also been made to tightly integrate agent-based modelling tools and GIS software, examples being the GeoTools Java library and the RePast GIS model (Brown *et al.*, 2005).

Multi-agent modelling as spatial simulation has been widely deployed in ecology, social, economic and environmental sciences. For example, agents can be used to simulate family activities in an artificial society, such as planting, harvesting, eating, birth, marriage, moving house and death (Kohler *et al.*, 2000). Polhill *et al.*, (2001), in a land use study, deploy agents to simulate land parcels for understanding rural land use changes, foreseeing the likely consequences of possible changes and their influences on future changes. In a study of modelling hydrologic processes by Reaney (2004), agents are deployed to trace the path taken by water through catchments. In a petrol price model by Heppenstall *et al.* (2005), agents act as petrol stations with each agent having broad control over its own pricing with variations in pricing being derived from both local and external factors.

3. Challenges in assessing the validity and usefulness of multi-agent models

In line with other forms of computational modelling, multi-agent models need to be evaluated to ensure that they are internally correct, perform as expected and can form a basis for decision-making. The appropriate terminology for such evaluations has been subject to considerable debate (e.g. Oreskes, 1994; Rykiel, 1996; Mitro, 2001; Mazzotti & Vinci, 2007). Emanating particularly from the ecological sciences, the term ‘verification’ refers to the correctness of the internal structure and working of a model whilst the term ‘validation’ refers to the model performance and its applicability to a subject domain. A further activity, that of ‘calibration’, is the adjustment of parameters and constants to improve model agreement with an observable reality (Rykiel, 1996). Mazzotti and Vinci (2007) point out that validation and calibration are integral processes in creating reliable models. In the context of this paper, verification concerns the correctness of a model such as its system diagrams, units of measurement, equations and initial states, whilst validation concerns the ability of the results from simulations *in silico* to be generalised to the real world, an integral part of this also being any calibration. This closer coupling of validation and calibration is necessary because a key outcome of multi-agent models is to study emergent behaviour. For many simulations, validity will reside in their ability to adequately model phenomena *ex post*, that is, to mimic to an acceptable

degree empirical data of phenomena that have already occurred or are occurring. Levels of plausibility and trust can thus adhere to simulations of future events and trends, or of interventions to manage or mitigate certain future scenarios (e.g. Batty et al., 2003b; Itami et al., 2003; Straatman *et al.*, 2004, Bennett & Tang, 2006; Ligmann-Zielinska & Jankowski, 2007). It is the assessment of validity and attendant calibration of multi-agent models which is at the core of this paper.

The main aim of multi-agent models is to explore complex spatio-temporal phenomena, in particular the emergence of macro patterns of behaviour from the micro levels of activity of large number of actors (O'Sullivan & Hacklay, 2000; Batty, 2005), often within intricately defined spaces (Puusepp & Coates, 2007). It is this very level of geographical complexity and emergent behaviours that raise methodological challenges in validating multi-agent models (Amblard *et al.*, 2005; Manson, 2007). Aspects that need to be considered are the stability or robustness of the emergent patterns, calibration of parameters, setting of initial state(s) and boundary conditions, and the propagation of error (Ginot & Monod, 2005). The problem of equifinality is also present. Ways of testing these rely heavily (though not exclusively) on sensitivity analyses (Saltelli *et al.*, 2000) in order to: calibrate parameters governing micro behaviour against available empirical data, model parameter errors and assess model sensitivity to the parameter phase space and initial state(s). However, complex systems can be nonlinear in their response to parameter changes, may have amplified effects as well as tipping points and thresholds (Crossetto & Tarantola, 2001; Phillips, 2003; Manson, 2007).

In order to illustrate some of these challenges, we present three short examples in which incremental changes have been made to only one parameter in each model; all other variables and initial states have been kept constant. The first, in Fig. 1, is a flocking multi-agent model in which each 'bird' strives to fly in the general direction of surrounding 'birds' without bumping into others. The field-of-view of each 'bird' is critical. When set at 45° the 'birds' only partially flock and gradually split into smaller groups. When set at 90° the 'birds' flock as a single group in flight patterns around the domain. With a 120° field-of-view the 'birds' become confused and although they stay together in the centre of the domain they appear to churn randomly. The second example, given in Fig. 2, is a stigmergic multi-agent model, that is, where the agents sense and

learn from their environment but also change it (stigmergy is a process of self-organisation through indirect communication). The classic example of this is an ant model where each 'ant' detects and follows pheromones but also deposits them. The angle over which an 'ant' can sense the pheromones attached to a lattice of nodes has been incrementally changed from 45° to 180°. This results in very different emergent patterns of pheromone concentration that reflect the travel patterns of the 'ants'. The third example, given in Fig. 3, uses cellular automata (CA), which whilst not technically a multi-agent model is close in concept to one (Rodrigues & Raper, 1999): each cell can act autonomously, CA can be used to study emergence in complex systems and CA can be implemented using software agents. Illustrated here is a three-population Schelling model of segregation (Schelling, 1971) that has been implemented on SpaCelle (www.spatial-modelling.info). Each final state (at 200 iterations) has been quantified using a global Index of Contagion (O'Neill *et al.*, 1988) as implemented in FRAGSTATS (www.umass.edu/landeco/) and which measures the tendency for classes to be aggregated (0% for random patterns, 100% for complete occupation by a single class). The parameter that has been incrementally changed is the minimum neighbourhood tolerance. As is illustrated, between 20% and 30% is a tipping point after which a high level of clustering replaces randomness. As the parameter further increases, there is a nonlinear return randomness.

[Figure 1 about here]

[Figure 2 about here]

[Figure 3 about here]

In these examples, we have only demonstrated model sensitivity to a single parameter. Usually there are a number of parameters that may need to be tested. Further complications arise where models are stochastic and therefore need to be tested not as a single run as in Figure 3 but by a large number of repeated runs for each parameter setting. Validation of multi-agent models can quickly become intractable (Batty *et al.*, 2003b) leading Batty and Torrens (2005) to argue for a more qualitative evaluation of a model's plausibility. The

solution proposed here is to develop generic agent-based services specifically for the validation of multi-agent models that harness the intelligence, interoperability and mobility of agent-based technologies. In the next section we discuss the nature of agent-based services which is then followed by the case study. The case study in Section 5 uses sensitivity analysis to help assess the validity of a multi-agent model and assist in its calibration.

4. Agent-based services

A service is understood in the general sense of rendering aid, help or doing work for someone else. Thus a software service is a piece of computer code which renders some form of assistance to a user in carrying out tasks. An obvious example would be a procedural wizard to assist in tasks such as: setting up a new database, importing or exporting data, customising views. Agent-based services are an enhancement of the type of procedural service just described in that the agent-based services can have autonomous behaviour, network mobility, goal directed behaviour and can work collaboratively. They can exhibit reasoning behaviour that can be both re-active to events and pro-active in achieving desired goals. In the spatial domain, agent-based services have been primarily deployed in data management and visualisation though some applications have extended to spatial decision support, Grid computing and spatial data quality analysis. For example, Tsou and Battenfield (2002) propose the use of agents as distributed services in GIS particularly for the integration of heterogeneous data sets. Purvis *et al.* (2003) used a multi-agent system to query and integrate distributed environmental information over a network. Sengupta and Bennett (2003) designed an agent-based framework to utilize online data and models for spatial decision support. Nute *et al.* (2004) developed NED-2 which is a decision support system that integrates a wide variety of modelling tools for forest ecosystem management. In these applications, agents are deployed either as online or offline tools. Li Y. (2006) has investigated online agent-based services for spatial data quality analysis in managing error and uncertainty for coastal oil spill modelling. Sengupta and Sieber (2007) have recently reviewed the literature on geospatial agents.

The complexity and near intractability of validating multi-agent models has been discussed in the previous Section. Agent technologies are well suited to

handling complexity (Jennings, 2000). The overall problem to be tackled can be decomposed into a number of autonomous agents each with its own capabilities and goal directed behaviour. The designed collaboration between the agents is the means by which the relationships between the decomposed elements of the overall problem can be managed. Thus agent-based services can themselves be engineered as multi-agent tools and thus, if necessary, developed and enhanced incrementally. The network mobility and interoperability of agents opens the possibility for agent-based services to be made available on the Internet as distributed components. This is the approach that underscores our investigation of agent-based services directed towards the validation of multi-agent models. The efficacy of such a solution has already been demonstrated in an investigation of network-resident agent-based services to provide data quality analyses for numerical simulation models that are loosely coupled with GIS (Li Y., 2006). As presented in the following case study, two collaborating agents have been designed as agent-based services for validating multi-agent models: one to carry out sensitivity analyses, the other to assist in model calibration. Although as discussed in the previous Section, a range of issues need to be addressed in establishing the validity of multi-agent models, the function of the agent-based services presented here, whilst not encompassing all conceivable aspects of model validation, nevertheless represent two key elements and are thus sufficient for a proof-of-concept.

5. Case study

The case study presented here centres around the modelling of wayfinding behaviour in the context of location-based services (LBS). LBS are defined as “the delivery of data and information services where the content of those services is tailored to the current or some projected location and context of a mobile user” (Brimicombe & Li, forthcoming). The modelled behaviours of wayfinding individuals, represented as agents, are derived from empirical studies of wayfinding behaviour for which important aspects of emergent patterns are known for a test locality (see Li C., 2006). The purpose of constructing a multi-agent model of wayfinding is to study emergent behaviours in other localities (real or planned) or in particular contexts. The multi-agent model therefore requires validation. To assist in this process, two classes of

agents have been developed as agent-based services: one to perform sensitivity analyses, the other to facilitate calibration. Both the multi-agent wayfinding model and the agent-based services for validation have been implemented using JACK (www.agent-software.com), an agent development environment supporting distributed applications using agent-oriented extensions to Java.

5.1. Theoretical basis of wayfinding using mobile devices

Wayfinding is one of the basic spatial activities undertaken by people frequently, and is purposive behaviour involving individuals and environments. The term 'wayfinding' can be defined as the process by which paths/routes are identified, determined and followed between an origin and a destination (Bovy & Stern, 1990; Golledge & Stimson, 1997). Wayfinding requires interactive behaviour between people and their environments. The attributes of both people and their environments influence how and how well wayfinding is achieved (Allen, 1999). During wayfinding activities, the environment is a dynamic source of information used by individuals in their decision-making processes. Furthermore, human wayfinding is often assisted by external aids such as maps, some forms of instructions and devices. With the development of mobile telecommunications and positioning technologies, wireless mobile devices have provided a new way of delivering spatial information to assist peoples' wayfinding. These technologies are at the heart of LBS where the supply of wayfinding information to mobile users is an important application. Such information can be accessed in a variety of communication modes, with more emphasis on tailoring to individual needs. Wayfinding assistance through tailored information to mobile devices is a key activity of LBS (Brimicombe, 2008). Some applications of wayfinding assistance provide a number of different information types as maps, text or voice; either singly or in combination. An important consideration of these applications must be to provide pertinent and timely information to users.

Studies of wayfinding activities assisted by LBS require a re-conceptualisation of wayfinding as human-environment interaction to include the technological dimension with a new focus on the dynamic interactions between individuals, mobile devices and environments (Li C., 2006) as

illustrated in Fig. 4. When encountering new environments as might be expected during wayfinding, people are likely to need a range of information for completing spatial tasks. Interaction with environments may include recognising and understanding characteristics of objects, localities and inter-relationship between elements in the environment. For the mobile human-computer interaction, the surrounding environment has started to be brought into consideration both through the design of context-aware devices and in the tailoring of information provision (Li & Willis, 2006). The complexity of the interactions and the real-time information transactions is raising important challenges for wayfinding research. Empirical studies have been carried out in immersive virtual urban environments (Li C., 2006; Li and Longley, 2006). These studies demonstrate the interaction concept of wayfinding and shows that individuals' wayfinding behaviours are influenced by: their specific location within the environment, the need for initial planning time, their usage frequency of the mobile device for assistance, their preferences for particular types of information. The empirical data used in this case study were obtained from these wayfinding experiments.

[Figure 4 about here]

5.2. A multi-agent model of wayfinding

Based on the interaction concept of wayfinding and the empirical studies described in the previous section, a multi-agent wayfinding model has been developed. The structure of this multi-agent model is shown in Fig. 5. Three types of agents are present in the model: '*Person*' agent, '*DecisionPoint*' agent and '*MobileDevice*' agent, shown in Fig. 5 as boxes A, B and C respectively. Each individual, represented by the '*Person*' agent, is an agent object that carries out wayfinding tasks and has behaviours regarding requests for information, information preferences, spatial learning and walking speed. There can be many '*Person*' agents launched into the environment. Meanwhile, each decision point (e.g. junction or landmark) on a road network is also developed as an agent object, referred to as '*DecisionPoint*' agent, which can provide the information related to it. This simulates the individual's acquisition of information about the environment. An individual's mobile device (e.g. mobile phone),

providing wayfinding assistance information on request, is represented by the 'MobileDevice' agent. This agent has rules for the release of information depending on what is requested by the individual. Thus individuals interact both with the environment and their mobile device during wayfinding activities. Furthermore, as they travel, each 'Person' agent maintains a record of its track, states and activities for later analysis.

[Figure 5 about here]

Within the model architecture, each agent is associated with one or more capabilities, plans and events. Capabilities define what an agent can do - its abilities or goals - with each capability providing a specific function. Plans define the sequence of actions that an agent can take in order to achieve a goal. Thus one or more plans support a capability. Plans can in turn be triggered by events which the agent then responds to. Capabilities, plans and events form the basis for an agent's reasoning behaviour which can be both goal directed (pro-active) and event directed (re-active). An agent can optionally have a database for both static and dynamic data.

A 'Person' agent is able to find its way (i.e. walking) along a road network from some starting point to a destination by means of its 'Wayfinding' capability. This capability is governed by plans concerning its starting point (*AtStartPoint*), arrival at the destination (*ArriveDestination*), finding a route between the two (*FindRoute*) and physically moving along it (*Move*). The arrival of the agent at a junction or landmark (*ArriveDP*) triggers the 'DPInfo' capability which retrieves information on the nature of that decision point from the 'DecisionPoint' agent. The communication between 'Person' agent and 'DecisionPoint' agent simulates the scenario of an individual perceiving their surrounding environment during wayfinding activities. If information is required whilst at a decision point to find or refresh the memory of a possible route, the 'MDInfo' capability is triggered which then requests wayfinding assistance information from the 'MobileDevice' agent. Depending on the nature of the request, governed by the 'RequestInfoFrmDevice' plan, different types of wayfinding assistance information such as maps and route instructions can be retrieved from a database (*MDKnowledge*) simulating an LBS response.

Although this is necessarily a very brief description of a multi-agent wayfinding model, it will be evident that there are a considerable number of parameters governing the behaviour of ‘*Person*’ agents who in groups share characteristics of spatial learning ability, preferences for different information types, time spent planning a route and the need to refresh the information during the wayfinding. Testing such parameters forms the basis of the case study of agent-based services to assist multi-agent model validation.

5.3. Structure of the sensitivity and calibration test agent-based services

In this case study, the agent-based services have been designed to fulfil two main tasks: to test the validity of the multi-agent model discussed above through sensitivity analyses, and to assist in model calibration. Each agent-based service may comprise a set of sub-agents that perform specific tasks with some sub-agents shared between services. This study only focuses on developing two prototype service agents: a sensitivity test agent and a calibration agent. Whilst there are many approaches to sensitivity analysis (Saltelli *et al.* 2000), this proof of concept is limited to a one-at-a-time (OAT) design. In the sensitivity analysis, parameters influencing object agent (i.e. ‘*Person*’ agent) behaviours are perturbed and the multi-agent wayfinding model repeatedly re-run in order to analyse the stability of the model. The appropriate value and bounds are then established for related variables in the model. Done manually this is laborious work but is efficiently managed by an agent-based service. For the calibration, the pattern of behaviour from the multi-agent model is matched against the empirical data. Parameters are incrementally changed until a fit is achieved. The variables used in this case study are the walking speed of individuals and planning time they need at each decision point. Following a full validation, the multi-agent wayfinding model can then be reliably deployed (to be reported on elsewhere).

These two agent-based services stand separately from the multi-agent model. They have the ability to be act as distributed components over a network which is one of the main features of remote agents discussed in Section 2. They are designed to communicate with the multi-agent wayfinding model and between themselves. These agent-based services take advantage of key features of agent-based technologies such as autonomous behaviour, network

mobility, goal directed behaviour and collaborative working. They exhibit reasoning behaviour that can be both re-active to events and pro-active in achieving desired goals.

One of the agent-based services is the '*SensitivityTest*' agent developed to carry out sensitivity testing of multi-agent models, the structure of which and its means of communication with the '*Person*' agent are given in Fig. 6. This agent has one capability which is to broker sensitivity test information (*SenInfoBrokering*) which has plans for running the multi-agent model reiteratively for sensitivity tests (*SenReStart*) and handling the sensitivity test information (*HandleSenInfo*). The '*SensitivityTest*' agent is also linked with a database (*SenKnowledge*). This database holds a range of data such as test parameters, test results and test performance. Furthermore, in order to establish the communication between the '*SensitivityTest*' agent and the multi-agent wayfinding model, a capability named '*CommServAgent*' has had to be added to the '*Person*' agent. This capability uses two plans for the communication. One plan is to request sensitivity test information of the '*SensitivityTest*' agent (*RequestSenInfo*), and another is to receive and process the test requirements from the '*SensitivityTest*' agent (*ProcessSenInfo*). The service can be invoked by a '*Person*' agent posting an event (*RequestVallInfo*) to activate the action of requesting sensitivity test requirements (*RequestSenInfo*). Iterative running of the multi-agent model in a sensitivity test is handled by the arrival '*Person*' agent at its destination (*ArriveDes*) which acts as a trigger for a new iteration (*SenReStart*). The '*Person*' agent's communication capability '*CommServAgent*' with its two plans can also be used to pass the results of model's sensitivity tests from the multi-agent model to the '*SensitivityTest*' agent.

[Figure 6 about here]

The other agent-based service is the '*Calibration*' agent which, as its name suggests, is to assist calibration for the multi-agent model. The overall structure of the '*Calibration*' agent is identical to the structure of the '*SensitivityTest*' agent (Fig. 6); therefore a detailed description of the '*Calibration*' agent is not required here. The '*SensitivityTest*' and '*Calibration*' agents have been developed as stand-alone validation tools that are separate from the wayfinding multi-agent

model though necessarily with communication links into it (Fig. 6). Unlike the 'DecisionPoint' and 'MobileDevice' agents which are integrated within the multi-agent wayfinding model and communicate with the 'Person' agent, these two validation service agents can operate independently. As services, they can either reside in the same computer with the 'Person' agent or in a different computer across a network. Developed using JACK, both 'SensitivityTest' and 'Calibration' agents have the ability to communicate remotely across a network. In other words, agent-based services and a multi-agent model can send events to each other over a network. It provides the potential that these agent-based services can be widely shared across a network by different multi-agent models. Such an open structure also makes it easy to develop further stand-alone validation agents in order to expand the range of agent-based services that can be called upon.

The flowchart in Fig. 7 illustrates the outline operating process of both multi-agent model and the agent-based services for model validation. After the initialization, there are two ways of operating the multi-agent model. One (shown as the left route in Fig. 7) is operating the model without validation service applied. Thus the 'Person' agent is activated to start the multi-agent model with its default parameters. When the model has halted the results are exported. The second way (shown as the right route in Fig. 7) is operating the model with a validation test. Different from the first way, the 'Person' agent is activated to start with a request for validation requirements. According to the information supplied by the agent-based service, the parameters of the model are set. The model is then run. When one run of the model is completed, the 'Person' agent re-sets the parameters according to the new requirements from the agent-based service and the model is re-started. When the whole validation test is finished, the test results are exported.

[Figure 7 about here]

5.4. Testing agent-based services

A test has been carried out using the multi-agent wayfinding model and the two agent-based services discussed in Sections 5.2 and 5.3. The test is intended as a proof-of-concept in deploying agent-based service to validate

multi-agent models. In this test, a simple road network is used as shown in Fig. 8. The spatial extent of this road network is approximately 400m × 400m. The task for each individual is to find one's way from point 'A' to point 'B'. In this test, at each junction, each '*Person*' agent will request wayfinding assistance information from their mobile device. The test is carried out in three parts: model sensitivity to walking speed, model sensitivity to planning time and calibration of planning time.

[Figure 8 about here]

The first part of the test is designed to investigate model sensitivity to individual walking speed during the wayfinding task. The multi-agent model aims to study wayfinding behaviour which can be influenced by a number of factors such as time used in requesting assistance from a mobile device, preferences for certain types of information, environment layout and landmarks. In order to focus on these aspects it is desirable that the model is not sensitive to walking speed. In order to choose an appropriate walking speed for the model, a sensitivity test is run using the '*SensitivityTest*' agent. In the test, the model is repeatedly run using different walking speeds. Task time, that is the completion time of a wayfinding task, is used as one indicator of the wayfinding model performance. As shown in Fig. 9 (a), the average value of task time becomes less sensitive to walking speed after 1.5 meter/second. Therefore, in considering the set up of walking speed in the model, the speed in the range of less than 1.5 meter/second should be avoided. In this model, the walking speed is set to approximately 1.5 meter/second (3.2 mile/hour) which also closely matches the empirical data (see Table 1).

Another test, using the '*SensitivityTest*' agent, is designed to investigate the model sensitivity to planning time at junctions during the wayfinding task. Planning time in wayfinding (denoted as the variable '*planning_time*') is one of the important effects in the wayfinding model. Time spent in route planning and decision-making can vary considerably depending on individuals and circumstances. In this model, the planning time is considered to be influenced by the complexity of junctions and the distance between the junctions and the destination. Through a sensitivity test, a better understanding can be gained of how the '*planning_time*' variable influences the model performance. Overall task

time is again used as the indicator of the wayfinding model performance. As results shown in Fig. 9 (b), the task time is less sensitive to the variable '*planning_time*' when it is in the range of 1.5 to 3.5 minutes. However, when the value of the variable '*planning_time*' is less than 1.5 minutes or greater than 3.5 minutes, the task time is more sensitive to the planning time as summarised in Table 1. This non-linear response of task time to planning time would not be evident without the sensitivity test and is important to know when assigning values in the model.

[Figure 9 about here]

[Table 1 about here]

The '*Calibration*' agent has been used in a test to perform a calibration of the planning time in the multi-agent model according to the sensitivity pattern and with regard to the empirical data. Within the multi-agent model some initial planning takes place as well as at each junction and is not a fixed amount but varies depending on junction complexity and length of route left. It also varies across groups of '*Person*' agents depending, for example, on their spatial learning ability. What is known from the empirical data is that for the task depicted in Table 1 the average overall planning time is 1.5 minutes. The '*Calibration*' agent incrementally adjusts the planning time parameters, as in a sensitivity test, until a fit with the empirical data is achieved. As identified during the sensitivity tests above (see Fig. 9), there is a range of values for the '*planning_time*' variable over which the model is comparatively stable, that is, perturbation of '*planning_time*' does not have a large effect on the model output. Therefore, the model calibration can be run on larger step sizes of relevant coefficients until coming close to the value supplied from the empirical data. On the other hand, when in the range that the model is more sensitive to the '*planning_time*' variable (such as the range with value less than 1.5 minutes), the model performance can be unstable. Consequently, the '*Calibration*' agent runs on much smaller step sizes of relevant coefficients in approaching the value provided via the empirical data. In this test, the empirical value of the average planning time is 1.5 minutes which is just between the more sensitive and less sensitive ranges. Therefore, the calibration should use smaller step

sizes for planning time up to 1.5 minutes and can use larger step sizes beyond (see Fig. 10).

[Figure 10 about here]

6. Conclusions

Validation and calibration are recurrent problems in multi-agent modelling. Such models are used to explore spatio-temporal phenomena with particular interest in emergent patterns of behaviour at the macro level from the micro levels of activity of large numbers of actors. The complexity of these models with large numbers of parameters that may have non-linear responses can make validation intractable. To create reliable multi-agent models, validation and calibration are integral processes. In the context of this paper, the closer coupling of validation and calibration is necessary because a key outcome of multi-agent models is to study emergent behaviour. Developed here has been the concept of using agent-based technologies to create agent-based services that assist in the validation and calibration of multi-agent models. Agent-based services are an enhancement of conventional procedural approaches in that they can have autonomous behaviour, network mobility, goal directed behaviour and can work collaboratively. They can exhibit reasoning behaviour that can be both re-active to events and pro-active in achieving desired goals. A case study involving a multi-agent of wayfinding behaviour using mobile devices has provided a proof of concept. Such agent-based services offer an efficient solution where large numbers of model runs need to be carried out. In this paper, the agent-based services are collaborative sets of agents that perform key tasks in the validation of multi-agent models, specifically sensitivity analysis and calibration. In the case study, the prototype agent-based sensitivity analysis and calibration services are implemented for a multi-agent wayfinding model. The case study demonstrates how agent-based services can be deployed for testing the robustness of emergent patterns through sensitivity analyses and multi-agent model calibration. Whilst in this paper agent-based services have been used to assist in validation, very similar agent-based services could be constructed to explore all the parameter spaces that result in emergent patterns of interest as this is an equally complex and time-consuming task. Agent-based

services thus have considerable potential for assisting in multi-agent modelling for complex spatial phenomena.

Acknowledgments

The authors would like to thank Renee Puucepp (Centre for Evolutionary and Computational Architecture, University of East London) for the examples of sensitivity analysis of flocking and stigmergic agents in Section 3.

7. References

- Adler, R.M., & Cottman, B.H. (1989). A development framework for distributed artificial intelligence. *Proceedings of the Fifth Conference on Artificial Intelligence Applications*. IEEE.
- Albrecht, J. (2005). A new age for geosimulation. *Transactions in GIS*, 9(4), 451-454.
- Allen, G. L. (1999). Spatial abilities, cognitive maps, and wayfinding: bases for individual differences in spatial cognition and behavior. In Golledge (Ed.), *Wayfinding Behavior: Cognitive Mapping and Other Spatial Processes* (pp. 46-80). Baltimore: The Johns Hopkins University Press.
- Amblard, F., Rouchier, J., & Bommel, P. (2005). Evaluation et validation de modèles multi-agents. In F. Amblard, & D. Phan (Eds), *Modélisation et Simulation Multi-Agents* (pp. 103-140). Lavoisier, Paris.
- Batty, M. (2005), *Cities and Complexity*. The MIT Press, Cambridge, MA.
- Batty, M., Desyllas, J., & Duxbury, E. (2003a). The discrete dynamics of small-scale spatial events: agent-based models of mobility in carnivals and street parades. *International Journal of Geographic Information Science*, 17, 673-697.
- Batty, M., Desyllas, J. & Duxbury, E. (2003b), Safety in numbers? Modelling crowds and designing control for the Notting Hill Carnival. *Urban Studies*, 40, 1573-1590.
- Batty, M., & Torrens, P.M. (2005). Modelling and prediction in a complex world. *Future*, 37, 745-766.
- Benenson, I., & Torrens, P.M. (2004). Geosimulation: object-based modelling of urban phenomena. *Computers Environment & Urban Systems*, 28, 1-8.
- Bennett, D. A., & Tang, W. (2006), Modelling adaptive, spatially aware, and mobile agents: Elk migration in Yellowstone. *International Journal of Geographical Information Science*, 20, 1039-1066.
- Bovy, P.H.L., & Stern, E. (1990). *Route Choice: Wayfinding in Transport Networks*. Kluwer Academic, Dordrecht.
- Brimicombe, A.J. (2008). Location-Based Services and GIS. In J. Wilson & A.S. Fotheringham (Eds), *The Handbook of Geographical Information Science*, Blackwell, Oxford: 581-595
- Brimicombe, A.J., & Li, C. (forthcoming) *Location-Based Services and Geo-Information Engineering*. Wiley, Chichester.

- Brown, D.G., Riolo, R., Robinson, D.T., North, M., & Rand, W. (2005). Spatial process and data models: Toward integration of agent-based models and GIS. *Journal of Geographical Systems*, 7, 25-47.
- Crosetto, M., & Tarantola, S. (2001). Uncertainty and sensitivity analysis: tools for GIS-based model implementation. *International Journal of Geographic Information Science*, 15(5), 415-437.
- Ferber, J. (2005). Concepts et méthodologies multi-agents. In F. Amblard, & D. Phan (Eds), *Modélisation et Simulation Multi-Agents* (pp. 23-48). Lavoisier, Paris.
- Franklin, S., & Graesser, A. (1997). Is it an agent, pr just a program? A taxonomy for autonomous agents. In M.J. Wooldridge, & N.R. Jennings (Eds), *Intelligent Agents III: Agent Theories, Architectures, and Languages* (pp. 21-35). Springer-Verlag, Berlin.
- Ginot, V., & Monod, H. (2005). Explorer les modèles par simulation : application aux analyses de sensibilité. In F. Amblard, & D. Phan (Eds), *Modélisation et Simulation Multi-Agents* (pp. 75-102). Lavoisier, Paris.
- Golledge, R.G., & Stimson R.J. (1997). *Spatial Behavior: A Geographic Perspective*. The Guilford Press, New York.
- Heppenstall, A.J., Birkin, M.H., & Evans, A.J. (2005). Optimising a hybrid agent-based system with application to the retail petrol market. *GeoComputation 2005*, Ann Arbor, Michigan, USA.
- Itami, R., Raulings, R., MacLaren, G., Hirst, K., Gimlett, R., Zanon, D., & Chladek, P. (2003), RBSim 2: simulating the complex interactions between human movement and the outdoor recreation environment. *Journal of Nature Conservation*, 11, 278-286.
- Jennings, N.R. (2000). On agent-based software engineering. *Artificial Intelligence* 117, 277-296.
- Kohler, T.A., Kresl J., West, C.V., Carr E. & Wilshusen R.H. (2000). Be there then: A modelling approach to settlement determination and spatial efficiency among late ancestral pueblo populations of the Mesa Verde region, U.S. Southwest. In Kohler T.A., & Gumerman G.J. (Eds.), *Dynamics in Human and Primate Societies* (pp. 145-178). Oxford University Press.
- Li, C. (2006). User preferences, information transactions and location-based services: a study of urban pedestrian wayfinding. *Computers Environment & Urban Systems*, 30, 726-740.
- Li, C. and Longley, P. (2006). A test environment for location-based services applications. *Transactions in GIS*, 10, 43-61.
- Li, C. and Willis, K. (2006). Modeling context aware interaction for wayfinding using mobile devices. *Proceedings Mobile HCI 06*, ACM, New York, 97-100.
- Li, Y. (2006). Spatial data quality analysis with agent technologies. In *Proceedings GISRUK 2006* (pp. 250-254). Nottingham.
- Ligmann-Zielinska, A., & Jankowski, P. (2007), Agent-based models as laboratories of spatially explicit planning policies. *Environment & Planning B*, 34, 316-335.
- Manson, S.M. (2007). Challenges in evaluating models of geographic complexity. *Environment and Planning B: Planning and Design*, 34, 245-260.
- Mazzotti, F.J., & Vinci J.J. (2007). Validation, verification, and calibration: using standardized terminology when describing ecological models. *Document*

- WEC 216, Wildlife Ecology and Conservation Department, University of Florida.
- Mitro, M.G. (2001). Ecological model testing: verification, validation, or neither? *Bulletin of the Ecological Society of America*, 82, 235-236.
- Nute, D., Potter, W.D., Maier, F., Wang, J., Twery, M., Rauscher, H.M., Knopp, P., Thomasma, S., Dass, M., Uchiyama, H., & Glende, A. (2004). NED-2: An Agent-Based Decision Support System for Forest Ecosystem Management. *Environmental Modeling and Software*, 19, 831-843.
- O'Neill, R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B., DeAngelis, B.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S., Dale, V.H., & Graham, R.L. (1988), Indices of landscape pattern. *Landscape Ecology*, 1, 153-162.
- Oreskes, N., Shrader-Frechette, & Belitz, K. (1994). Verification, validation, and confirmation of numerical models in the earth sciences. *Science*, 263, 641-646.
- O'Sullivan, D. (2008). Geographical information science: agent-based models. *Progress in Human Geography*, 32, 541-550.
- O'Sullivan, D., & Hacklay, M. (2000). Agent-based models and individualism: is the world agent-based? *Environment & Planning A*, 32, 1409-1425.
- Parker, D.C., Manson, S.M. & Berger, T. (2002). Potential strengths and appropriate roles for ABM/LUCC models. In D.C. Parker, T. Berger & S.M. Manson (Eds), *Meeting the Challenge of Complexity: Proceedings of the Special Workshop on Agent-Based Models of Land-Use/Land-Cover Change*, CIPEC/CSISS, Santa Barbara, 6-12.
- Phillips, D.J. (2003). Sources of nonlinearity and complexity in geomorphic systems. *Progress in Physical Geography*, 27, 1-23.
- Polhill, J.G., Gotts, N.M., & Law, A.N.R. (2001). Imitative Versus Non-Imitative Strategies in a land Use Simulation. *Cybernetics and Systems*, 32(1-2), 285-307.
- Pontius, R.G.Jr., Walker, R., Yao-Kumah, R., Arima, E., Aldrich S., Caldas M., & Vergara, D. (2007). Accuracy assessment for a simulation model of Amazonian Deforestation. *Annals of the Association of American Geographers*, 97(4), 677-695.
- Purvis, M., Cranefield, R., Nowostawski, M., Carter, D., & Bush, G. (2003). A multi-agent system for the integration of distributed environmental information. *Environmental Modelling & Software*, 18, 565-572.
- Puusepp, R., & Coates, P. (2007), Simulations with cognitive and design agents. *International Journal of Architectural Computing*, 5, 100-114.
- Reaney, S. (2004). Determining the origin of channel flow in a semi-arid catchment: the use of agent based modelling techniques in hydrology. *Geophysical Research Abstracts*, 6, 06001.
- Reitsma, F., & Albrecht, J. (2005). Implementing a new data model for simulation processes. *International Journal of Geographical Information Science*, 19(10), 1073-1090.
- Rodrigues, A., & Raper, J. (1999), Defining spatial agents. In A.S. Camara & J. Raper (Eds), *Spatial Multimedia and Virtual Reality* (pp. 111-129), Taylor & Francis, London.
- Rykiel, E.J. (1996) Testing ecological models: the meaning of validation. *Ecological Modeling*, 90, 229-224.
- Saltelli, A., Chan, K. & Scott, E.M.. (2000). *Sensitivity Analysis*. Wiley, Chichester.

- Schelling, T.S. (1971), Dynamic models of segregation. *Journal of Mathematical Sociology*, 1, 143-186.
- Sengupta, R., & Sieber, R. (2007). Geospatial Agents, Agents Everywhere *Transaction in GIS*, 11(4), 483-506.
- Sengupta, R.R., & Bennett, D.A. (2003). Agent-based modelling environment for spatial decision support. *International Journal of Geographic Information Science*, 17(2), 157-180.
- Straatman, B., White R., & Engelen, G. (2004). Towards an automatic calibration procedure for constrained cellular automata. *Computers Environment & Urban Systems*, 28, 149-170.
- Tsou, M.H., & Buttenfield, B.P. (2002) A dynamic architecture for distributed geographic information services. *Transactions in GIS*, 6, 355-381.
- Wooldridge, M. (1997). Agent-based software engineering. *IEE Proc. Software Engineering*, 114, 26-37.
- Wooldridge, M., & Jennings, N. (1995). Intelligent agents: Theory and practice. *The Knowledge Engineering Review*, 10(2), 115–152.

List of Figures and Tables

Fig. 1. Three instances of emergent behaviour (after 150 iterations) for a flocking multi-agent model based on incremental changes to the field-of-view parameter.

Fig. 2. Four instances of emergent patterns (pheromone concentration at nodes after 500 iterations) for a stigmergic multi-agent model based on incremental changes to the angle-of-sensing parameter.

Fig. 3. Sensitivity analysis of emergent patterns (after 200 iterations) for a three-population Schelling model of segregation (cellular automata) based on incremental changes to the minimum neighbourhood tolerance parameter and as measured by a global Index of Contagion: (a) emergent patterns of segregation, (b) the effect as measured using Index of Contagion at 10% increments.

Fig. 4. Conceptual framework for wayfinding using mobile devices.

Fig. 5. The structure of the agent-based wayfinding model (DP = decision point, MD = mobile device).

Fig. 6. The structure of the agent-based sensitivity test: the sensitivity test agent is contained within the box; beyond the box is the link into the wayfinding multi-agent model through the '*Person*' agent.

Fig. 7. Flowchart of the operating process.

Fig. 8. The road network used for the test of agent-based services

Fig. 9. The results from sensitivity tests; (a) wayfinding task time according to walking speed, (b) wayfinding task time according to planning time.

Fig. 10. Changes of step sizes within calibration test depending on overall model sensitivity.

Table 1

The sensitivity test outcomes of walking speed and planning time variables