David Hales
Bruce Edmonds
Emma Norling
Juliette Rouchier (Eds.)

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Multi-Agent-Based Simulation III

4th International Workshop, MABS 2003
Melbourne, Australia, July 2003
Revised Papers

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Preface

This volume presents revised versions of the papers presented at the 4th International Workshop on Multi-agent Based Simulation (MABS 2003), a workshop federated with the 2nd International Joint Conference on Autonomous Agents and Multi-agent Systems (AAMAS 2003), which was held in Melbourne, Australia, in July 2003. In addition to the papers presented at the workshop, three additional papers have been included in this volume (Robertson, Noto et al., and Marietto et al.).

Multiagent Based Simulation (MABS) is a vibrant interdisciplinary area which brings together researchers active within the agent-based social simulation community (ABSS) and the multiagent systems community (MAS). These two communities have different, indeed somewhat divergent, goals. The focus of ABSS is on simulating and synthesizing social behaviors in order to understand observed social systems (human, animal and even electronic) via the development and testing of new models and concepts. MAS focuses instead on the solution of hard engineering problems related to the construction, deployment and efficient operation of multiagent-based systems.

Increasingly however – and this was evidenced at AAMAS 2002 – the MAS and ABSS communities have much to learn from each other. Real human societies are generally self-organizing, highly scalable, robust and open, and the ABSS community has developed a sizable set of techniques, observations and models that give insight into some of the mechanisms that underpin these kinds of systems. However, ABSS has not concerned itself with applying these techniques to solve engineering problems. Conversely, the MAS community is concerned with creating working agent systems that solve real problems. This focus has forced many to abandon experimentation with large-scale systems (thousands of agents) composed of smart autonomous agents (e.g., complex adaptive learners) due to the lack of traditional techniques (and/or computational resources) for managing such complexity.

This difference of emphasis often precludes dialogue between ABSS and MAS researchers and practitioners, but MABS workshops have a track record of providing a major forum for such dialogue to occur. The work presented in various sections of the AAMAS 2002 main conference demonstrated a keen interest in the use of learning and adaptation combined with large-scale agent societies — increasingly, sociological issues such as cooperation, trust and power hierarchies are being broached from the engineering perspective. In light of this, the 2003 MABS workshop returned to its original aim, asking researchers from each community to identify problems and challenges for those in the other community.

The MABS workshop offers a potential linkage (shared vocabulary and methodology) between social scientists and MAS researchers, and at MABS 2003 we attempted to focus on the development of this linkage. To this end, Giovanna Di Marzo Serugendo was invited to open the proceedings with a presentation of her work on utilizing self-organization to produce solutions to software engineering problems. A paper based on this talk can be found in this volume. MABS 2003 was the fourth workshop in the MABS series. The first two were organized as federated workshops of ICMAS 1998 and ICMAS

2000. The third MABS workshop was federated with AAMAS 2002 (which subsumed the ICMAS series). The first MABS workshop, held in Paris at ICMAS 1998, had as its aim "to develop stronger links between those working in the social sciences, for whom agent based simulation has the potential to be valuable research tool, and those involved with multi-agent simulation, for whom the social sciences can provide useful concepts and exemplars". The proceedings were published by Springer in LNAI 1534, in a volume called *Multi-Agent Systems and Agent-Based Simulation.* The second MABS workshop, held in Boston at ICMAS 2000, extended this development, and provided substantial discussions. The presentations focused on lessons of social simulation for DAI, on the supporting and reporting of social simulation modeling and on social simulation-based software applications. These were published by Springer-Verlag in LNAI 1979, in a volume called *Multi-Agent-Based Simulation.* The third MABS workshop, held in Bologna at AAMAS 2002, continued the aim of developing and supporting links between social science and Multi-Agent Systems practitioners via the medium of multiagent-based simulation. Additionally, the workshop echoed a specific AAMAS 2002 topic: "interactions between people and agent technology." The workshop proceedings were published by Springer-Verlag in LNAI 2581, called *Multi-Agent-Based Simulation II.*

This fourth MABS workshop continued the tradition of high-quality presentations, discussion and debate coupled with a multidisciplinary approach, and we thank all those who made it possible, including the AAMAS general and local organizers who ran an incredibly professional conference and provided us with excellent workshop facilities.

Finally, we must also thank Alfred Hofmann and the Springer team for again supporting the dissemination of this latest installment of the MABS series.

Manchester, September 2003

David Hales
Bruce Edmonds
Emma Norling
Juliette Rouchier

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Engineering Emergent Behaviour: A Vision

Giovanna Di Marzo Serugendo

Centre Universitaire d'Informatique, University of Geneva
24, rue Général-Dufour
CH-1211 Geneva 4, Switzerland
Giovanna.Dimarzo@cui.unige.ch

Abstract. Today's application tend to be more and more decentralised, pervasive, made of autonomous entities or agents, and have to run in dynamic environments. Applications tend to be social in the sense that they enter into communication as human people, and engage into discovery, negotiation, and transactions processes; autonomous programs run their own process, interact with other programs when necessary, but each program lives its life, and a global behaviour emerges from their interactions, similarly to what can be observed in natural life (physical, biological or social systems). Tomorrow's applications are more and more driven by social interactions, autonomy, and emergence, therefore tomorrow's engineering methods have to take into account these new dimensions. Traditional software engineering will not be adapted to this new kind of applications: they do not scale, they do not enable the definition of local behaviours and drawing of conclusions about global behaviours. The scope of this paper is to determine today's and tomorrow's application domains, where such a sociological behaviour can be observed. Starting from the observation of natural life (natural mechanisms used for self-organisation, for anonymous communication, etc), we then discuss how these natural mechanisms can be translated (or have an artificial counterpart) into electronic applications. We also consider software engineering issues, and discuss some preliminary solutions to the engineering of emergent behaviour.

Keywords: Self-organisation, emergent behaviour, swarm intelligence, software engineering.

1 Introduction

The applications of today, such as the WWW, P2P systems, or those based on spontaneous or wireless networks, have the characteristic to be decentralized, pervasive, and composed of a large number of autonomous entities such as personal assistants, and agents. They run in highly dynamic environment, where content, network topologies and loads are continuously changing. In addition, they comprise a social dimension, i.e., the entities engage interactions, discover themselves, negotiate, and perform transactions.

These characteristics are also those which one finds in the self-organising systems we can see in nature, such as physical, biological and social systems. Indeed, self-organising systems have the characteristic to function without central

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control, and through contextual local interactions. Each component carries out a simple task, but as a whole they are able to carry out complex tasks emerging in a coherent way through the local interactions of the various components. These systems are particularly robust, because they adapt to the environmental changes, and are able to ensure their own maintenance or repair.

The majority of the applications of today then have certain characteristics of the self-organisation, to begin with the WWW itself, but also the Grids, P2P storage systems, e-purses, or ad-hoc routing. In certain cases, the complexity of the application is such, e.g. world scale, that no centralized or hierarchical control is possible. In other cases, it is the unforeseeable context, in which the application evolves or moves, which makes any supervision difficult. Among the applications of tomorrow, much of them will be biologically inspired: self-organising sensors networks, allowing the control of aerospace vehicles, or of dangerous zones; but also storage facilities, or operating systems facilities, which, like the human nervous system, controls in a transparent way significant functionalities [8].

There is currently an awakening that modern applications can gain (in robustness, and simplicity) if they are developed by following the principles of self-organisation which one finds in nature. To simulate and imitate nature in the electronic world constitute a first step. However, it is necessary to go beyond a simple translation of the natural paradigms. Mechanisms of interaction specific to the (electronic) applications have to be defined, as well as development methods making it possible to design components having their own local goal and whose interaction will make emerge the desired global result.

The challenges to take up in this field relate to the design, and the development of applications which "work by themselves": how to define a global goal; how to design the components and their local functionality knowing that the global goal is not a local sum of functionality; which will be the interactions between components, and how to check that the desired result will emerge during the execution. The traditional software engineering techniques are insufficient, since they are based on interfaces fixed at design time, or well established ontology. As for current methodologies, they only make it possible to define a global behaviour when it is a function of the behaviour of the various parts.

We present first self-organising systems taken from natural life, then we review some emerging self-organising electronic systems, finally we give an insight on how such applications can be engineered.

2 Self-Organising Systems

Self-organising systems are made of ***many interconnected parts*** *whose* ***local interactions,*** *within a given* ***environment,*** *give rise to* ***emergent*** *properties, or behaviour, observable at the level of the global system only.*

The particularity is that the emergent properties do *not* arise out of the description of an individual component; or that the emergent global behaviour is *not* encoded in the local behaviour of entities. Other characteristics of self-organisation include: *no central control,* the system is composed of several parts acting as peers, i.e., there is no top-down control, or top-down description; the system evolves *dynamically* with time; the system *interacts with its environment,* it modifies it and is consequently affected by its modification. More generally, the field of complex systems studies emergent phenomenon, and self-organisation [2].

Domains of natural life where we can find emerging behaviour include physical, biological and social systems.

2.1 Physical Systems

A thermodynamic system such as a gas of particles has emergent properties, temperature and pressure, that do not derive from the description of an individual particle, defined by its position and velocity. Similarly, chemical reactions create new molecules that have properties that none of the atoms exhibit before the reaction takes place [2].

2.2 Biological Systems

In biology, the human nervous system, or the immune system transparently manages vital functions, such as blood pressure, digestion, or antibodies creation. The immune system defends the body from attacks by undesired (foreign) organisms. It is made of many different kinds of cells that circulate the body looking for foreign substances. The immune system cells recognise and respond to substances called antigens: “self” antigens are part of the body, while infectious agents, recognised as “non-self” have to be eliminated[1] .

2.3 Social Systems

Social insects organise themselves to perform activities such as food foraging or nests building. Cooperation among insects is realised through an indirect communication mechanisms, called stigmergy, and by interacting through their environment. Insects, such as ants, termites, or bees, mark their environment using a chemical volatile substance, called the pheromone, e.g., as do ants to mark a food trail. Insects have a simple behaviour, and none of them alone “knows” how to find food, but their interaction gives rise to an organised society able to explore their environment, find food, and efficiently inform the rest of the colony. The pheromonal information deposited by insects constitutes an indirect communication means through their environment.

Human societies use direct communication, they engage negotiation, build whole economies, and organise stock markets. Another interesting point is related to the structure of connectivity between individual human beings, also called social networks, where one can reach anyone else through a very small number of connections [12].

[1] National Institute of Allergy and Infectious Diseases, http://www.niaid.nih.gov/publications/

3 Self-Organising Applications

Nature provides examples of emergence, and self-organisation. Likewise, applications of a near future, as well as current distributed applications, by their heterogeneity, scale, dynamism, absence of central control, gain to be designed so that they organise themselves autonomously.

3.1 Self-Organising Sensor Networks

Self-organising wireless sensor networks are used for civil and military applications, such as volcanoes, earthquakes monitoring, or chemical pollution checking. Sensor networks consist of self-organised nodes, which dynamically need to set up (maybe several times) an ad-hoc P2P network, once they are deployed in a given area. They need as well to calibrate themselves in order to adapt to their environment [13]. Sensor networks benefit of recent technology enabling integration of a complete sensor system into small-size packages, as for instance the millimeter-scaled motes provided by the SmartDust project[2].

3.2 Smart Materials

Maintenance or security systems can now be part of clothes, walls, or carpets. Such electronic textile contain intertwined sensor chips or LEDs that form a self-learning and self-organising network. Applications of such smart materials include intruders detection (by pressure on a carpet); visitors guidance through a trail of LEDs; or identification of escape routes in emergency situations[3].

3.3 Autonomic Computing

Based on the human nervous system metaphor, IBM Autonomic computing initiative considers systems that manage themselves transparently wrt the applications. Such systems will then be able to self-configure, self-optimize, self-repair, and protect themselves against malicious attacks [8].

3.4 Ambient Intelligence

Ambient intelligence envisions seamless delivery of services and applications, based on ubiquitous computing and communication. Invisible intelligent technology will be made available in clothes, walls, or cars, and people can freely use it for virtual shopping, social learning, micro-payment using e-purses, electronic visas, or traffic guidance system [4]. Ambient intelligence requires low-cost and low-power designs for computation running in embedded devices or chips, as well as self-testing and self-organising software components for robustness and dependability.

[2] http://robotics.eecs.berkeley.edu/ pister/SmartDust/

[3] http://www.infineon.com

4 Engineering Emergent Behaviour

The central question related to the software engineering of self-organising applications is: how to program single agents so that, when taken as a whole, they self-organise. The engineering of self-organising applications needs means to define a global goal, and to design local behaviours so that the global behaviour emerges. This is difficult, because the global goal is *not* predictable as the sum or a function of the local goals. Consequently, the verification task turns out to be an arduous exercise, if not realised through simulation.

Traditional practice in multi-agent systems introduce basic techniques for autonomously interacting or retrieving information, such as agents coordination, service description, or ontology. However, these techniques rely on pre-progammed interaction patterns, preventing adaptation to unexpected environmental changes. Current engineering practices, which directly address self-organisation, consist in designing distributed algorithms according to the social insect metaphor (e.g., digital pheromone) [3]. More recently, specific electronic interaction mechanisms are being defined, and middleware technology developed, that will help the development of self-organising applications. However, verification and whole engineering methods remain open issues.

4.1 Coordination and Control Using Stigmergy

Analogies with natural life have been used and direct translation of natural mechanisms into the electronic world have already been implemented. For intrusion detection and response in computer networks [5], the immune system serves as a metaphor for detecting intruders, and the stigmery paradigm is used for responding to the attack. Mobile agents permanently roam the network in order to locate abnormal patterns of recognition. Once an attack is detected, a digital pheromone is released so that the source of attack can be located, and a response to the attack can be given.

The stigmergy paradigm serves also for manufacturing control [7]. Agents coordinate their behaviour through a digital pheromone. In order to fulfill manufacturing orders, they use mobile agents that roam the environment, and lay down pheromonal information.

4.2 Interaction Models

In addition to the digital pheromone, which is the artificial counterpart of the natural pheromone used by the ants, it is necessary to establish new electronic mechanisms directly adapted to the applications. They can be based on *tags,* a mechanism from simulation models. Tags are markings attached to each entity composing the self-organising application [6]. These markings comprise certain information on the entity (functionality, behaviour, etc.) and are observed by the other entities.

Alternatively, the *Co-Fields* model drives agents behaviour as would do abstract force fields. Agents and their environment create and spread such fields in the environment. A field is a data structure composed of a value (magnitude of field), and a propagation rule. An agent then moves by following the coordination field, which is the combination of all fields perceived by the agent. The agents moves modify the fields, which in turn modify the agents behaviour [10].

4.3 Middleware Approaches to Self-Organisation

Acting as middleware layers, coordination spaces provide uncoupled interaction mechanisms among autonomous entities, which input data into a common tuple space, and may retrieve data provided by other entities. On top of the basic coordination environment, several enhancements have been realised in order to support self-organisation. The TOTA environment (Tuples On The Air) propagates tuples, according to a propagation rule, expressing the scope of propagation, and possible content change [9].

Anthill is a framework for P2P systems development based on agents, evolutionary programming, and derived from the ant colony metaphor. An Anthill distributed system is composed of several interconnected nests (a peer entity). Communication among nests is assured by ants, i.e., mobile agents travel among nests to satisfy requests. Ants observe their environment, and are able to perform simple computations [1].

4.4 Verification

Non-linear systems are difficult to understand because they cannot be described analytically, using equations that can help predict the system behaviour. Generally, the system is simulated through a model, and some results are obtained from the execution of the simulation.

Simulation is an essential tool to anticipate the results and to determine parameters. However, it is not sufficient to guarantee a correct result when a whole system is built using self-organising principles. Self-organisation itself ensures robustness and adaptability. In addition, one can give to the components the means of avoiding situations who could harm their correct execution. For instance, the concept of tags, explained higher, could vehicle a proof [11] and a specification, of the correct operation of a peer entity, that could be checked before interactions take place.

5 Conclusion

This paper advocates that modern and future distributed applications gain to be considered and engineered as self-organising applications. Traditional software engineering methodologies are no longer adapted to this new kind of software, which is running in highly dynamic environments, pervasive, large-scale, resource-constrained, and heterogeneous. In addition to interaction techniques, or middleware favoring self-organising behaviour, we need software engineering techniques for design, test, and verification, based on mathematical theory enabling the establishment of local goals, given the expected global behaviour [8].

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Employment Decisions Supporting Organizations of Autonomous Agents

Foster McGeary and Keith Decker

Computer and Information Sciences
University of Delaware
Newark, DE 19716, USA

Abstract. A key aspect of organization is that one or more agents perform tasks at the direction of another, supervising, agent. We model a set of individual actors using intelligent agents. These agents self-interestedly choose products to produce and to consume. Our initially-identical autonomous agents self-interestedly form organizations, with the employing and employed agents performing separate value computations. Use of agents, rather than statistical demand and supply functions, enables direct computation of every action by every agent, permitting the tracing of activity to the boundedly rational behavior of intelligent agents. Actions which incur costs, such as choosing others with whom to transact, that are often modeled using equation-based quantities in other work, are here performed by the computer code needed to achieve the desired result. A key feature of this work is that these self-reflective agents balance thinking about what they will do with actually doing it.

1 Introduction

The workshop invited discussion of methodologies and techniques linking Agent-Based Social Simulation ("ABSS") with Multi-Agent Systems ("MAS"). This paper is such a discussion. We describe a set of identical, limitedly rational, self-interested autonomous agents, each of which reasons about its own resource utilization. Each agent has an explicit welfare function to value consumption of various artifacts, and the agent uses technologies to produce the artifacts. When appropriate, agents form organizations to improve their independently-derived welfare. All agent activities are performed within a context that addresses the bounded rationality described by March and Simon [11] and the limited rationality of Russell and Wefald [16], both as interpreted in a MAS.

These agents link the ABSS and MAS worlds because they are based in large part on foundations found in economics, but implemented within a general-purpose MAS. The MAS provides a structure for passing messages among agents and the desire to maximize an objective function in a social context provides messages for the agents to pass. The agents are artificial and provide a ready set of tools with which to exercise and study economics within a general equilibrium model based in methodological individualism. In particular, these agents contribute to the study of economics because the economic computations used are forced to conform to fairly robust conditions of being recursively computable. These agents must calculate, or obtain from another agent, all the data

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they need, a requirement not often addressed. We take this to be an ABSS application supported by MAS.

This paper addresses how these agents employ one another in the course of each agent acting self-interestedly and organizing to apply technologies for its own betterment. We perform experiments evaluating the benefits accruing from organizations that are voluntarily formed by the agents, thus exhibiting self-organizing behavior. We further investigate the ability of the mechanisms used by the agents to support such organizations in situations with many agents. Our MAS is Internet-based, supporting scalable numbers of agents, and this paper demonstrates how the agents we have designed operate with moderate numbers of participating agents.

2 Related Work

In our work, protocols and employment contracts control inter-agent behavior. Three well-known approaches to controlling agents are those proposed by (1) Jennings and Wooldridge, who emphasize an "agent oriented" approach to problem solving, by (2) Tennenholtz, who specifies conventions and "laws" that agents should obey, and by (3) Rosenschein and Zlotkin, who provide conventions for negotiation under certain pure forms. We do not review agent-based commerce decision tools principally because we deal here with agents that actually make decisions, as opposed to those that collect and pre-process data for humans.

Work by Wellman, by Sandholm and Lesser (e.g., [18]), and by others too numerous to cite, is extensive with respect to particular aspects of the dealings of buyers and sellers. Mostly, these authors address in depth the terms of exchange for extant artifacts. However, we are also as concerned with how agents self-interestedly form the organizations that make the artifacts as we are with their exchange, and because our focus is broader it is premature to apply the full force of these focussed analyses. In WALRAS [2], for example, there is central control of the bidding. Our agents would not be able to employ such an algorithm until they were self-interestedly able to (1) determine that central control was self-interestedly rational and (2) select and compensate the central controller. In strategic breach, Sandholm and Lesser [17] rely on enforcement of breach penalties, but do not explain how their agents self-interestedly evolve and support the institutions that enforce those penalties. Our long-term desire is to provide mechanisms by which our agents develop and provide resources to the institutions they use, conditioned on their having computed that the whole effort (building and operating the institutions they use) is in their best interests. Our agents are still a long way from availing themselves of the benefits of, for example, levelized-commitment contracting.

Jennings and Wooldridge design agents to solve a particular problem and have a preference for applying agents to problems that are nearly decomposable [10]. They argue that most complex systems are nearly decomposable. With decomposability, each agent is assigned a special role to fulfill while acting on behalf of the problem solver. Jennings and Wooldridge note the need for balance among the agents, but regard it as a problem for the agents' designers, not the agents. We regard the balancing as a problem for the agents to solve, and, most importantly, we assume there is not *one* balancing problem to be solved, but *as many problems as there are agents.* We use homogeneous agents as a base that will allow us to examine causes and effects and to separately study issues attributable to differences in agent endowments and tastes.

Tennenholtz with others [19, 13,21,6] see agents as social constructions that should obey social laws, which laws they develop. This approach is derived from state-based agents and addresses the question "Wouldn't it be easier for all agents to obey certain rules rather than to negotiate them repeatedly?" Three basic cases arise: (1) anarchy, with no laws or conventions, (2) Social Conventions, which dictate agent behavior, and (3) Social Laws, which rule out certain behaviors but do allow agents to select from among a set of lawful behaviors. Social Conventions and Social Laws trade the efficiency of individual agents for the efficiency of a group of agents. Our agents are intended to be general purpose agents that can survive and prosper in a variety of artificial worlds (sets of resources, technologies, and number of agents), so conventions that are conditioned on the world in which they are applied would have to be worked out for each such world. As Tennenholtz shows the computation of optimal laws to be NP-complete, it is clear they cannot be applied generally, even in situations where agents "agree" to abide by the outcome.

Rosenschein and Zlotkin [15] outline a third approach to controlling agents, with the nature of the domain in which the agents operate shaping the protocols used among agents. Domains are characterized as "Task," "State," or "Worth" oriented. Protocols are designed to facilitate the exchange of commitments among agents within that domain. The agents outlined below are "Worth Oriented" in this framework, and therefore, it is argued, must have a "A *symmetric cooperative* situation [...] in which there exists a deal in the negotiation set that is preferred by both agents over achieving their goals alone. Here, both agents welcome the existence of the other agent." (p. 105) States where there is *conflict* are ruled out for Worth-oriented domains because the two-agent world has a solution where one agent simply "pays off" the other.

3 Agent Domain

For us, the agent's domain is the total environment within which the agent operates, and includes all the forces and facts with which this self-interested decision-making agent must contend. One force, the agent welfare function, and one set of facts, the available artifact production technologies, now receive special attention.

Agents consume artifacts to get utility. For this paper, agent welfare (utility) is

$$U = \sum_{t=0}^{\infty} d_t \sum_{i=1}^{n} \frac{a_{t,i}}{s_{t,i}} \left[e^{s_{t,i}X_{t,i}} - 1\right] \tag{1}$$

where n is the number of artifacts of interest to the agent; $X_{t,i} \geq 0$ is the quantity of artifact i consumed during time interval t; $d_t > 0$ is a discount factor, equal to e^{-rt} with continuous discounting at the constant discount rate r; $a_{t,i} > 0$ is the relative weight of the artifact; and $s_{t,i} < 0$ is a saturation rate controlling the rate of decrease in marginal utility for artifact i. Agents trade for artifacts $X_{t,i}$ or construct $X_{t,i}$ using technologies.

Agents construct artifacts by applying technologies to raw materials and other artifacts. For an organization, the difference between the costs of producing an artifact and the artifacts received in trade for the produced artifact accrue to the owners of that organization, and can be applied to maximize the utility (as in (1)) of those owners. The expectation is that the agents will form organizations we will call "firms," that the differences between costs and receipts will be "profits," and that the profits will be used to maximize the utility of the owners of the firms.

A food artifice confines final artifacts to have the names of food products and provides a common domain for exposition. We therefore constructed a Virtual Food Court ("VFC") and let the agents in it maximize their welfare (utility) with resource-bounded rationality. The VFC [12] is implemented in DECAF [3,4,8,9]. For this paper, all agents use the same welfare function, with time-invariant weights and rates.

Technologies are implemented by agents applying Skills to Artifacts. The technologies are readily computable as they have a recursive structure, with raw materials, which are not themselves manufactured by technologies, treated as Artifacts. The number of operations in a technology may be large, and the operations (skill applications), in some cases, must be executed in particular orders for the artifacts to be constructed. Agents will therefore sometimes need to schedule activities to ensure that technology operations are applied in the proper order. In simple terms, our technologies are just pre-computed task networks, i.e., plans. We've renamed and regrouped some of the concepts to fit our model. Skills are the basic operations (or Hierarchical Task Network (HTN) primitive tasks) that have preconditions and effects, and technologies are compound tasks in the standard Erol, Hendler, Nau [5] formalization of HTN planning. For this paper all agents possess the same skills, so employers do not reason about skill availability among candidate agents. Each skill, as an interim matter, nominally requires a well-known average amount of work to complete, and that amount is used for computing payment for the skill.

4 Agent's Approach to the Problem

The basic problem is a constrained optimization problem that the agent divides into smaller problems, corresponding to the long run, the short run, and moving between the long and short runs. The agent addresses these three facets concurrently, with attention shifting to the most interesting (utility enhancing) computations.

Equation 1 specified the agent's utility. We view the long run as that target allocation of artifacts that ensues once the short run is over. The long run is intended as a computational simplification to deal with the infinite sum in (1). The long run begins at some date in the future when current "everyday" problems no longer affect the level of consumption and deals with the utility equation beginning with period $t = l + 1$. The short run deals with periods up through l. Thus we re-craft (1) as

$$U = \sum_{t=0}^{l} d_t \sum_{i=1}^{n} \frac{a_{t,i}}{s_{t,i}} \left[e^{s_{t,i} X_{t,i}} - 1\right] + \sum_{t=l+1}^{\infty} d_t \sum_{i=1}^{n} \frac{a_{t,i}}{s_{t,i}} \left[e^{s_{t,i} X_{t,i}} - 1\right]. \tag{2}$$

Sectionalization is helpful for two reasons. The short run portion, up to period l, is of finite size, and can be addressed by conventional problem-solving algorithms. The long run portion, after period l, can be collapsed into a smaller problem.

4.1 The BDI Paradigm

A Belief-Desires-Intention ("BDI", [7]) approach to agent behavior is useful for explaining how agents shift focus periodically as they allocate resources to most productive uses. The agent's welfare function (1) determines for the agent how well it has done, and entails that an agent "wants" to maximize the present value of utility. As our agents have infinite lives, there is no endpoint from which to track backwards, so we postulate a "long term" expectation for the agent, and call this the agent's "Desires." Note that an agent's Desires change as its estimate of what is achievable by it changes.

We assign to the short run the agent's current calculation about what it will do "now." The performance of particular tasks and actions from its behavior repertoire is what an agent will undertake to achieve the long run plan. The schedule of these tasks and actions are similar to "Intentions" in the BDI framework. Intention computation involves the agent's purchasing choices, its proactive investment choices, and its choices of what employment arrangements to accept.

Finally, "Beliefs" covers the identifiers and numeric values the agent uses to perform the computations that establish its desires and intentions. Beliefs are the parameters (whether the names of other agents, the expected duration of particular actions, or the anticipated price of an artifact) that, when applied to the constrained optimization of the utility function, provide the agent with, respectively, its long run plan and its short run agenda of DECAF tasks and messages.

4.2 Meta Viewer

It is the MetaViewer portion of the agent that decides when it is time to place into the short run candidate actions to be acted on. For example, when it is time to eat, the agent selects a restaurant, a short run decision. Once the agent receives the restaurant's menu, it makes other short run decisions, such as whether to stay at the restaurant and what to order. It would be foolish to balance the cost of each and every item for dinner against each and every other use of the agent's resources. MetaViewer is what focuses the agent's decision consideration in situations where the agent needs to make decisions.

4.3 Consumption

The long run identifies actions the agent will find useful to perform in a general sense; the short run selects actions to perform in a specific sense. MetaViewer moves (or copies) actions from the long run section to the short run section when it identifies actions "ripe" for attention. By setting aside the short run part of (2), agents can concentrate on computing the long run part. We let $U1$ be the artifact consumption pattern on a typical day $\tilde{t}$ once the long run is reached.

$$U1 = \sum_{i=1}^{n} \frac{a_{\tilde{t},i}}{s_{\tilde{t},i}} \left[e^{s_{\tilde{t},i} X_{\tilde{t},i}} - 1 \right] . \tag{3}$$

The long run portion of (2) becomes the product of $U1$ and a present value of an annuity factor. The short-run portion is tractable: n classes of artifacts for l periods.

Recall that the original inspiration for the BDI model is Bratman [1]. Pollack summarizes his claim as “rational agents will tend to focus their practical reasoning on the intentions that they have already adopted, and will tend to bypass full consideration of options that conflict with those intentions” [7] This is precisely what we are doing with the long term/MetaViewer/short term. Pollack further observes that “It has been generally accepted for many years that agents cannot possibly perform optimizations over the space of all possible courses of action [20]. Bratman’s Claim is aimed precisely at helping reduce that space to make the required reasoning feasible.” The traditional formalization of BDI [14] states “A deliberation function such as *maximin* or *maximizing expected utility* is then defined for choosing one or more best sequences to perform at a given node.”

5 The Source of Value in Employment

Value exists in employment for technologies where additional workers increase output faster than investment, decreasing the average cost of the artifact produced. This is textbook accounting and economics; we use cost accounting terms to describe the process. Each agent can compute the costs of producing the various artifacts in its domain because it has the requisite information: (1) Each technology shows required skills and artifacts, (2) Skills specify the artifacts needed to perform them, (3) Skill durations can be estimated and, recursively, (4) Similar data exist for supporting artifacts.

5.1 Value of an Employee

Production varies with employment because employees supply the skills that produce the artifacts. Each technology specifies the skills required to operate it, and so employers compute the amount of direct labor (work) needed as the product of the desired level of output and the direct labor required per unit of output.

Assume the pizza-making skill requires an oven, and this $40,000 oven needs to be replaced after producing 10,000 pizzas, for an average $4.00 direct cost per pizza. If the employer makes 100 pizzas per day, the oven lasts 100 days, and the simplest interest cost would show carrying costs on $20,000 for 100 days of $1,000 at 18 percent interest, which is $0.10 per pizza. At 10 pizzas per day the oven lasts 1,000 days, and the interest cost would be $10,000 (without compounding), or $1.00 per pizza. Doing the right thing depends on the answers to empirical questions such as “Is $0.90 per pizza important to the agents?” and “Does the cost of finding employees/employers justify it?”

5.2 Value as an Employee

If these were the only costs, the agent consuming 10 pizza a day would have an isolated own-production cost of $5.00 (plus 10 minutes of its skill time) per pizza versus a purchase cost of between $4.10 and $5.00 (plus some cost for worker compensation) from an agent selling pizzas.

Now suppose that the employer and employee agent both value their time at $1 per minute (of course, these values only appear in the solved version of the problem, and are not available while the agents are still reasoning). Pizzas will sell for between $14.10 and $15.00 each. While many solutions are possible, at $14.50 the oven owner Agent J could pay employee Agent K $ 145.00 to produce 12 pizzas. Agent K could then buy the 10 pizzas it wanted. It would have worked 120 minutes, rather than 100, but it would not have incurred $40 (equal to 40 minutes) of oven depreciation, and so would have an extra 20 minutes of time for other uses. Agent J would have its money back from Agent K and have an additional 2 pizzas to sell (or consume itself), for an additional $29 in revenue, or 29 minutes of additional other consumption. Both agents would deduct from their apparent profits the time spent finding each other and negotiating the employment agreement to determine if a boundedly rational result was obtained.

6 Employment and Organization

Our definition of an organizational structure recognizes only "firms" and asserts that the contractual structure of the firm is the tree of relationships defined by contracts that bind individual agents to their managers. The task structure of a firm is the tree of individual task assignments that fulfill organizational purposes, and "dotted lines" would represent intra-firm messages that do not flow along solid lines representing contracts. Note that we allow firms to form self-interestedly, intending later to apply organizational theories to analyze them. We do not design organizational structures for the agents to populate.

6.1 Employment Structure

The DECAF environment uses task "plans" to specify agent behaviors. These DECAF tasks are the finest level of detail into which *plans* can be divided. These plans, together with the knowledge that all agents have access to the same task plans, allow agents to identify particular individual DECAF tasks (Java methods) that may be performed by any of the VFC agents. An agent desires to have another agent perform one of these DECAF tasks at its direction when the total cost of recruiting, directing, and paying that other agent is less than the benefits from that performance.

6.2 Scrip

Contracts form the basis for making explicit the nature of the messages. The principal focus of this paper is the sending of messages where the employee agent is to perform a skill using artifacts provided by its manager, with the result of the skill application being returned to the manager. In some cases, agents may find it desirable to use scrip to assist in the creation of a contract, and all cases examined in this paper use scrip.

Scrip is used as a form of currency, but with the backing of the issuer instead of the backing of the government issuing a currency. In our case, scrip is used to make the conditions of exchange easier to negotiate on the grounds that a stated amount of scrip, redeemable for artifacts of the holder's choice, reduces the need to tailor contracts to a fixed set of artifacts for each transaction. For the studies performed here, scrip does not expire and is not transferable among the agents.

6.3 Production Employment Contract

Where an organization frequently requires agents to perform skills for it and where the agents that desire to perform those skills for such an organization frequently desire to do so, there is an opportunity to form a contract with a longer term than a simple one-time exchange contract. We discuss such "Production Employment Contracts" here.

Suppose Agent J wants another agent to perform some of the skills innate to VFC agents, but has no firm idea of exactly which skills and in what order the skills will be required. Suppose that Agent K is willing to perform the skills. Suppose further that the parties have agreed that these are fair exchanges and now need to create the contract. This sequence of actions would achieve the operational aims of Agents J and K:

1. Agent J sends the proposed contract to Agent K.
2. Agent K signals Agent J that the contract is accepted, putting the contract into force.
3. Agent K begins performing the following loop:
    a) Agent K listens for commands from Agent J.
    b) Agent K receives a message containing artifacts and identifying the skill to apply to them.
    c) Agent K applies the designated skill to the artifacts to produce an outgoing artifact.
    d) Agent K sends its outgoing artifact to Agent J.
    e) Agent J sends the proper payment for the designated skill to Agent K.
    f) Agent K indicates its receipt of the payment.
    g) Agent K evaluates whether the contract is terminated.
4. The contract expires.

Each step above could have associated with it a message from one agent to the other, with the agents' respective duties for each of the intended messages in the contract.

VFC agents use the above sequence of actions for their contracts.

6.4 Compensation

Recall (Sect. 3) that agents have the ability to determine the utility of consuming a unit of artifact. Agents also have the ability to compare the costs of purchasing the artifact with the cost of making it. These abilities, together with a proposed compensation rate, permit an agent to determine whether it is better off accepting an offer to work for the proffered rate or to use the available work time to operate its sole proprietorship.

An agent finds novel product offerings as it visits restaurants in search of products it does not produce itself. It will offer to work for an Agent J when it believes that Agent J could be the low-cost producer of a product which it does not produce but which it desires. The amount of work an agent will intend to provide depends on the quantity of the desired artifact that appears in its short term purchase intentions. There is no benefit in obtaining more scrip than that needed to purchase the intended quantity.

Employer agents are free to increase the level of compensation to employee agents for new skill assignments, and we provide a message for this purpose. Employers may terminate employees at will, or simply stop sending skill assignments. Employee agents can reject work when it is not in their own best interest. When a new low-cost producer is found for a product, consuming agents begin to reduce their intentions to accumulate the scrip of prior low-cost producers (i.e., they quit).

7 Employment Protocol

We start our discussion of the employment protocol with the employee because it is the employee-agents that discover a willingness to work for the employer-agents. This occurs because employers offer artifacts that employee-agents wants to consume, provided, of course, that the prospective employee finds the terms of exchange at least as good as terms available elsewhere. The terms of exchange are embedded in the wage rate to be paid, the time to be worked, and the prices charged for artifacts. Had we started with the employer, we would have needed to provide a mechanism for identifying those agents with a current desire for the products of the employer-agent.

7.1 The Employee Perspective

The agents we use search for low-cost suppliers of artifacts, the artifacts being used to enlarge the utility produced according to (1). An agent that includes consumption of Artifact I in its desires will form an intention to consume instances of that Artifact when the net present value of its expenditures for the Artifact produce more utility than the utility produced by other applications of those resources. This is consistent with the standard exhortations of economic theory.

The agent consuming artifacts will choose as the preferred source for each artifact class that "restaurant" at which it expends the fewest resources for it. Recall that each agent has access to all technologies. The consuming agent computes the present value of the time it would expend to produce an artifact. Also recall that each agent issues its own scrip. Absent a market for scrips the minimum wage rate that a consuming agent requires from an employing agent is computable. One agent, the employee-buyer agent k, is willing to work for another agent, an employer-producer agent j, if the employer is the low-cost producer for some artifact in the set of artifacts that the worker agent desires at the minimum wage. Assuming there is one artifact, numbered i, for which this is true, the conditions are:

$$\begin{aligned} \exists w_{t,j,k} \in \Re \mid \{ \; & w_{t,j,k} \geq \arg\min_{i \in Art} w_{t,j,k} \geq \frac{P_{t,i,j,k}}{E_{t,i,k}} \\ \wedge \; & w_{t,j,k} \geq \arg\max_{n \in Ag} w_{t,m,k} \geq \frac{P_{t,i,m,k}}{E_{t,i,k}} \} \end{aligned} \tag{4}$$

where, at time t for time interval t,

- $w_{t,j,k} \geq 0$ is the wage rate paid by agent j to k for work performed by k for j,
- $P_{t,i,j,k} \geq 0$ is the price of artifact i charged by agent j to agent k for purchases,
- $P_{t,i,m,k} \geq 0$ is the price of artifact i charged by agent m to agent k for purchases,
- $E_{t,i,k} \geq 0$ is the employee-buyer's estimate of the resources, measured in its own time, required to produce the artifact i,
- *Art* is the set of Artifacts with prices known to agent k and which are in the set of Artifacts Desired by agent k, and
- Ag is the set of agents that have provided a menu to agent k.

The prices agent k uses in its calculation are the most recent that it has. As we do not require agents to guarantee prices for any length of time, all prices could have changed.

7.2 The Employer Perspective

Final consumption artifacts are transferable once only, so employers must produce all the final consumption artifacts they offer for sale. An employer therefore provides, for purchase by its employees, sufficient instances of the artifacts to continue to attract those employees. While employers need not assign particular workers to skills used in making the particular artifacts that that individual employee wishes to obtain from the employer, each employer must make such assignments in the aggregate in order to retain those employees.

There is a self-balancing element to this situation that can be exploited by both workers and producers to reduce the burden of matching the availability and utilization (supply and demand) of skill performance (labor) by agents. Specifically, since each agent knows precisely how much of each artifact class offered by the employer it wishes to consume at the prices and wages offered by the employer, it can translate this demand into the amount of skill performance it wishes to perform for the employer. Similarly, each employer can assemble the artifact-demand and labor-supply amounts for the agents interested in working for it to derive the total demand for its artifacts at the prices it has chosen.

The employer knows (1) the buyers for its artifacts are the agents holding its scrip, (2) a portion of the demand schedule for its artifacts, (3) one set of labor supplies for its production needs, and (4) the full technologies for all needed artifacts. The producer can then decide upon the artifacts to produce, the prices to charge, and the agents to employ. These employers thus have sufficient data to attempt “profit maximization.”

7.3 Wages and Prices

Recall that Agent J agrees to become an employee of Agent K because Agent J believes that the scrip to be received for performing skills for Agent K can be exchanged for artifacts, and that those artifacts will provide more utility to Agent J than would spending the same time performing skills for Agent J’s own sole proprietorship. Agent K’s believes that employing and paying Agent J produces more utility for it than performing the skills itself (or leaving the operations un-performed). After the agreement is formed, however, changes occur in the environment, and the intentions of self-interested agents may change accordingly.

As the agents continue to visit restaurants and make employment offers to other restaurants, they may identify a new low-cost supplier for an Artifact I – this happens when an Agent C offers Agent K a wage that is better than the minimum wage. This supplier/employer is now Agent K’s preferred supplier and also Agent K’s only possible employer for supplying the scrip income to purchase Class I artifacts at Agent C’s restaurant. Employee Agent K disentangles itself from Agent J by sending a message to terminate its interest in receiving skill assignments (i.e., it quits).

Similarly, employers need to replace high wage employees with lower wage employees as the latter identify themselves. Task assignments will be made according to the low cost workers, but note that the employers will be constrained by the workers. The constraints arise because Buyer/Employee agents will have a good idea of how much work they will want to perform for each of their employers. Desires indicate desired consumption levels, which are readily translated by wage rates into desired levels of work. Identification of this work level by employer is needed because of the assumed inability to trade scrip. Excess scrip provides no value to employees, so providing work in exchange for it is undesirable.

7.4 Essential Protocol Details

Calling the consumer/worker agent “Worker” and the producer/employer agent “Manager,” the agents exchange a variety of messages. There are three contexts in which messages are most relevant to employment. First, every agent is a consumer and engages in information collection by exchanging messages with “restaurants” operated by other agents. Second, workers, by “visiting” producers, accumulate prices charged by those producers for their artifacts. These prices form the basis of the calculations outlined in Sect. 7.1 and in (4). Each Worker W with a Desire for a particular class of Artifact will notify, through the protocol, the restaurant it is visiting (Producer P) of the minimum wage needed to be paid to Worker W by Producer P to make Producer P the preferred supplier of an artifact, and thus a desirable employer to Worker W. The worker does not wait for a response; the producer sends its message when it self-interestedly determines that it is interested in retaining the services of the worker agent.

Third, a producer indicates its interest in a worker by sending it a message with a wage rate and a list of the skills that it wants to be able to assign to the worker. Finally, skills get applied operationally. The employer sends a message identifying the skill to be performed, the wage to be paid, and includes, as part of the message, the artifacts needed to perform the skill. The worker-agent either terminates the contract and returns the supplied artifacts to the producer or performs the skill and returns the modified artifact to the producer. If the worker agent requires a higher wage than that being offered, it would restart the protocol by quitting and re-applying for work.

8 Simulation Results

We defined an agent class using DECAF, with each agent as a separate instance of this class, operating as a stand-alone Java program, running as an independent Unix process. Each agent operated a sole proprietorship and was either self-sufficient (did not hire other agents nor visit the sole proprietorships of other agents) or was an an organizing agent, with the ability to hire employees other than itself. The agents had fifteen different final consumption Artifacts from which to choose. Twenty-two intermediate manufactured (plus five raw material) artifact classes support production of the fifteen final consumption Artifacts. The Utility we report is from (1), although the “per-capita” graphs show only the un-discounted utility. In all experiments we instantiated agents across the 4-CPU nodes of a multi-processor cluster[1] and let them try to maximize their individual welfare. In the eight-agent cases the agents were located on a single node. In

[1] NSF Grant No. IIS-9812764 supported development of DECAF. The present work was also funded in part by National Science Foundation Grant No. IIS-9733004. The simulations used computers provided under NSF grant CDA-9703088.

Table 1. Cases Examined

Case	Features
A	8 Self-sufficient Agents (no hiring of other agents)
B	8 Organizing Agents (will work for or hire other agents)
C	96 Organizing Agents (will work for or hire other agents)
D	96 Self-sufficient Agents (no hiring of other agents)

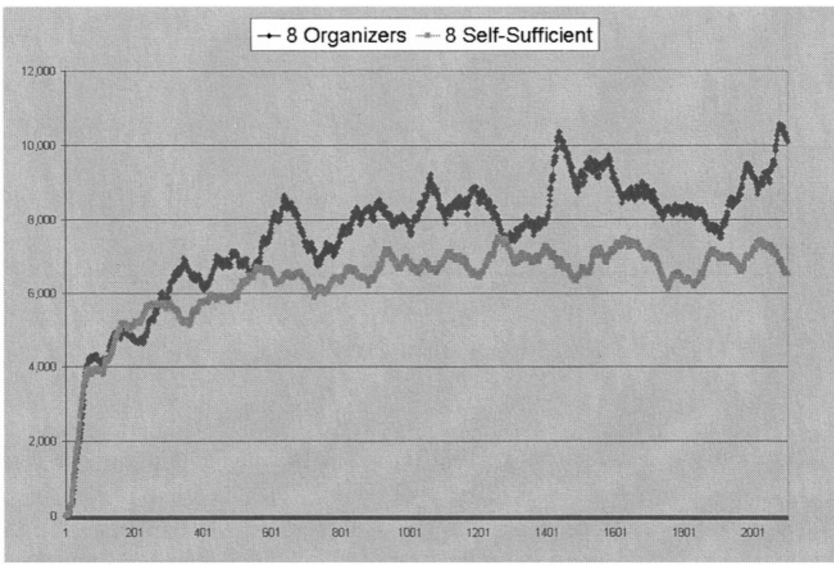

Fig. 1. Smoothed Average Daily Utility: Case A vs. Case B

the 96-agent cases there were eight agents instantiated on each of 12 nodes. Results for the first 2100 days are shown.

Table 1 lists the four simulation experiments we discuss here. Our intent at this point was to determine whether the underlying technologies and behavioral mechanisms we have built allow the agents to organize self-interestedly.

Comparing Case A and Case B was to illustrate the increase in utility achievable through small groups of agents interacting self-interestedly. The Fig. 1 shows average per-agent utility for the eight organizing agents in Case A (the higher, darker line) and for the eight self-sufficient Case B agents (the lower, lighter line). The two lines appear to overlap initially, but close inspection shows that the organizing agents experience less daily utility in the initial periods because they spend resources visiting each other, obtaining information, and registering for employment. As the simulations progress, organizing agents find that they can work for one another, allowing the employer agents to specialize their production in particular Artifact classes. As discussed in Sect. 5, agents that specialize use (and replace) their capital stocks faster than do the self-sufficient agents, resulting is lower expenditures of resources per unit of output. This is the mech-

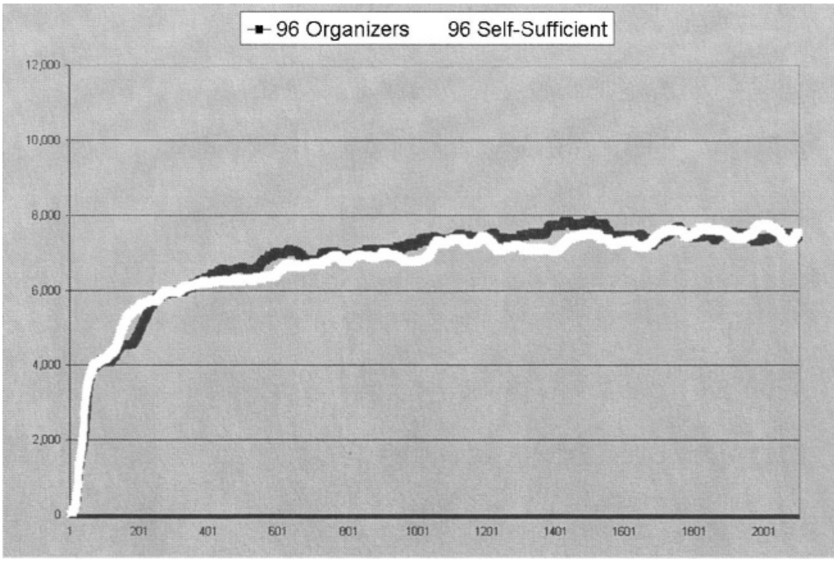

Fig.2. Smoothed Average Daily Utility: Case C vs. Case D

anism that allows organizers to out-perform the self-sufficient agents as measured by (1) utility.

The Fig. 2 shows the same measure as Fig. 1, but for the case where ninety-six VFC agents are active. The 96-agent organizing case shows a marginal 1.5 % improvement over the self-sufficient comparator (the white line) at the end of 2100 days on a net present value basis (that is, on the basis of (1) used to drive the decisions). This was unexpected as we thought the agents would scale better than this. We will examine this further below, and mark it as a topic for future study.

We compare Case A with Case D to determine whether there are hidden issues in scaling from few (eight) to many (ninety-six) agents. This is Fig. 3. We expect the inclusion of additional nodes into the experiments to have only minimal effect for self-sufficient agents. Since the agents have no substantial interactions with each other in the self-sufficient case, the only effects should be due to additional demands on the communication facilities of the cluster. We interpret Fig. 3 to confirm our expectations and conclude that the differences between the two lines in Fig. 3 should be regarded as statistical in nature, attributable to the difference in the number of agents and to the non-deterministic events that differentiate individual experiments in this type of simulation.

Cases B and C (few and many organizing agents) show how well our organizing mechanisms scale to larger sets of agents. The single 8-agent organizing case we report did appreciably better than did the 96-agent case. Even though it has greater variance, the darker (8-agent) line in Fig. 3 is to be preferred to the lighter (96-agent) line. Notice, however, that the relation between the 8-agent and 96-agent cases for organizing agents does not resemble that shown for the self-sufficient agents – the smaller group of organizing agents seems to consistently out-perform the larger group.

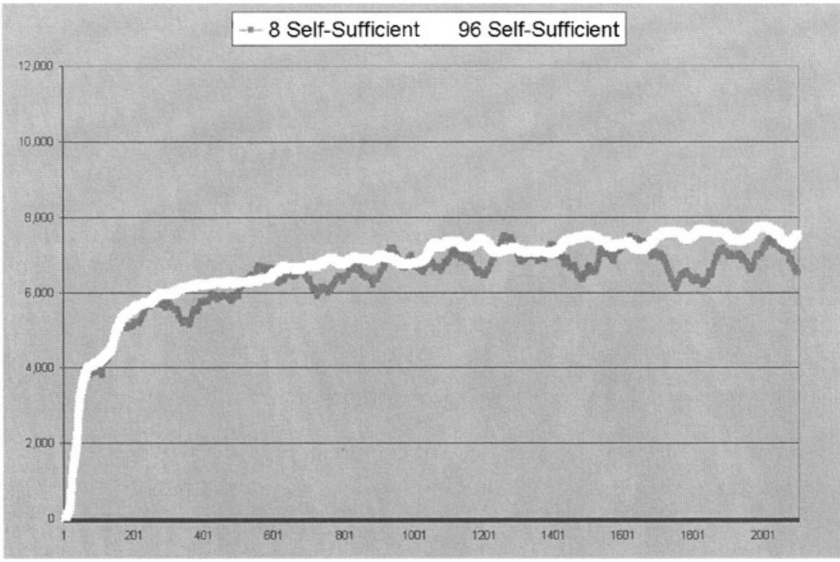

Fig. 3. Smoothed Average Daily Utility: Case A vs. Case D

9 Discussion

Possible causes of the high variance of few-agent runs relative to their many-agent counterparts and of the poor scaling performance are: (1) insufficient analytical procedures are available to the agents, (2) the "economy" formed by the agents requires additional self-interest-enhancing contractual features to be stable, and (3) the variance is inherent to agents that have no socially-derived institutions. Our long-term program addresses all three. The mutual dependencies among the agents shape the near term research program.

Agents forming employer-employee relationships are mutually dependent. The extent of the dependency is quite surprising for the agents examined here. Whenever scrip is non-transferable, employees and customers are the same agents. Employers can determine how much work each agent wants to perform by examining the orders which that agent places as a customer, but only if the agent's orders are not scrip-limited. Orders are *not* scrip-limited when the total order (recognizing the issue that items are in integral numbers) is less than that agent's scrip balance. The scrip balance is stored in the employer's banking function. Simply put, if the employee agent spends all its scrip, then it likely wants to perform more work to earn more scrip. Otherwise, it is to the right of the vertical line in Fig. 5, and does not want to accept additional skill assignments.

Firms operate by producing to maintain target inventory levels. The firms generate scrip in the accounts of their employees. For our agents, scrip allows a reduction in the coordination cost of aligning the production and consumption of artifacts, with inventories existing as buffers. There is thus a transactions demand for these buffers, and it is necessary for the employer to assure that sufficient stocks of the artifacts are kept to allow the employees to make their purchases according to the Desires of the employees.

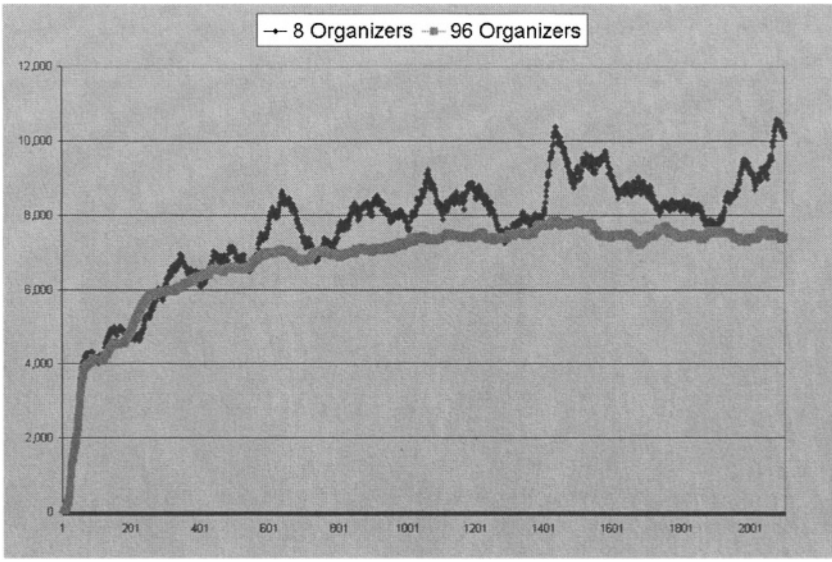

Fig.4. Smoothed Average Daily Utility: Case B vs. Case C

All of these issues, however, can be addressed through the proper exchange of information between the would-be employee and the would-be employer. The employee *can estimate* the amount of work it *currently* wants to provide using textbook economic analysis, which we cover in below. For the experiments reported here, the agents use a "hand-to-mouth" paradigm for their scrip income, intending to spend all available scrip up to the level determined by their Desires. This means (a) that employers need not strategize about the benefits to be gained from the store-of-value use of scrip by the employees, and (b) that employees will presume to receive the indicated scrip for the purposes of computing their Desires. Employers will than set inventory targets sufficient to meet the aggregate daily artifact demands of their owner and their employees/customers.

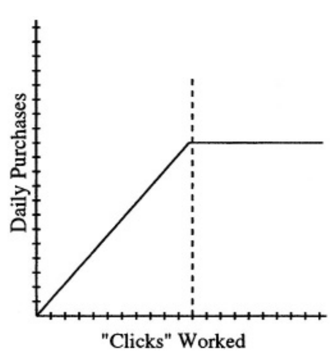

Fig.5. The Employment/Consumption Relation

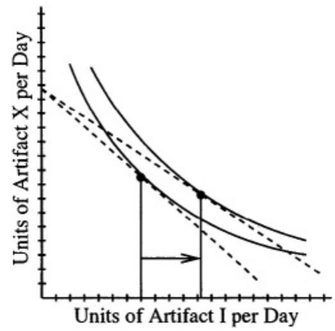

Fig. 6. Analysis of Employee Quitting

Even though the dependency is ephemeral, with agents changing relationships based on self-interested calculation, there are opportunities for agents to use information gained from one agent to exploit another agent until such time as that other agent becomes aware of the changed situation. Currently, Agent K will quit working for Agent J when Agent C has offered to employ Agent K at a wage that allows Agent K to purchase Artifact I in greater quantity than it can while working for Agent J given the wage that Agent J pays and the prices Agent J charges for Artifacts. Agent K quits based on the analysis depicted in Fig. 6. (An economics textbook will contain a technical discussion of the indifference curve analysis represented by Fig. 6.) The dotted lines show, for the two dimensions of the graph, combinations of Artifact X and Artifact I that can be obtained by Agent K depending on whether it works for Agent J (the line closer to the origin) or for Agent C (with a lower price and thus further from the origin). The dotted lines intersect the vertical axis in the same place because we assume the price of Artifact X does not change. What happens is that Agent C offers Agent K a lower effective price for Artifact I, increasing Agent K's demand for Artifact I and, if Agent K does a complete calculation (including updating its Desires), decreasing Agent K's demands for all other artifacts.

Upon accepting Agent C's offer, Agent K has no need for additional scrip from Agent J, and so it resigns its position and informs Agent J of the wage and income needed to make Agent K indifferent to working for Agent C or Agent J. Both actions are self-interested on Agent K's part. (Resigning stops messages assigning work that Agent K does not intend to accept. Informing Agent J of minimal conditions for re-hire prevents offers below this level from being sent, and the cost of sending this information is incrementally small, as (a) non-message passing computations were already incurred in performing the analysis of the offer from Agent C and (b) it is easily appended to the resignation message.)

10 Future Work

Our principal thrust in the current investigation was the creation of agents that could and would form employment relations with one another. We have succeeded in this, but our performance reminds us of a dog walking on two feet – not everyone finds the achievement useful and the result is seldom graceful. The ungracefulness stems from the large day-to-day variations in utility, variations which we know (from the form of (1)) reduce the level of utility. The usefulness of the achievement is measured by how often the overall question ("Are we doing the Right Thing?") is answered affirmatively.

The results and discussion above point immediately to several topics for further work to explicate the behavior witnessed in the experiments. The agents did not scale well in going from few to many agents, and we shall investigate this with great vigor. Similarly, the variation in daily utilities was larger than expected, and required the smoothing to show differences in the average performance of the agents in the various cases. The primary contributor to the variance was the frequent appearance of days in which particular agents did not consume *any* Artifacts. Further work will investigate how to improve the algorithms used to select restaurants in the face of rapidly changing employment conditions.

11 Conclusion

Our Multi-Agent System of self-interested autonomous agents improves the welfare of individual agents through reasoned exchanges of resources. While this is common with human agents, here we demonstrate it with a modest number of artificial intelligent agents. Thus, our work produces advances on two fronts. First, being able to have arm's-length exchanges of computational resources, without the need to understand the motivations or operations of the other party to the exchange, contributes to the building of large, robust Multi-Agent Systems. Second, we contribute to the demonstration that multi-agent approaches, together with today's computer hardware, are beginning to enable detailed models of aggregate economic behavior using explicit models of individual behavior.

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Towards Verification and Validation in Multiagent-Based Systems and Simulations: Analyzing Different Learning Bargaining Agents*

Keiki Takadama[1,2], Yutaka L. Suematsu[2,3], Norikazu Sugimoto[4], Norberto E. Nawa[2], and Katsunori Shimohara[2]

[1] Tokyo Institute of Technology
4259 Nagatsuta-cho, Midori-ku, Yokohama 226-8502 Japan
keiki@dis.titech.ac.jp

[2] ATR Human Information Science Labs.
2-2-2 Hikaridai, "Keihanna Science City" Kyoto 619-0288 Japan
{keiki,yutaka,eiji,katsu}@atr.co.jp

[3] Graduate School of Kyoto University
Yoshida-Honmachi, Sakyo-ku, Kyoto 606-8501 Japan
leon@symlab.sys.i.kyoto-u.ac.jp

[4] Nara Institute of Science and Technology
8916-5, Takayama-cho, Ikoma, Nara 630-0101 Japan
norika-s@is.aist-nara.ac.jp

Abstract. *Verification and validation* (V&V) is a critical issue in both multi-agent systems (MAS) and agent-based social simulation (ABSS). As the first step towards V&V methods for MAS and ABSS, this paper investigates whether different computational models can produce the same results. Specifically, we compare three computational models with different *learning mechanisms* in a multiagent-based simulation and analyze the results of these models in a bargaining game as one of the fundamental examples in game theory. This type of V&V is not based on the *between*-models addressed in conventional research, but on a *within*-model. A comparison of the simulation results reveals that (1) computational models and simulation results are minimally verified and validated in the case of ES(evolutionary strategy)- and RL(reinforcement learning)-based agents; and (2) learning mechanisms that enable agents to acquire their rational behaviors differ according to the knowledge representation *(i.e.,* the strategies in the bargaining game) of the agents.

Keywords: Verification and validation, multiagent-based simulation, comparison of different models, learning mechanism, bargaining game

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1 Introduction

One of the common critical issues in both multi-agent systems (MAS) and agent-based social simulation (ABSS) is *verification and validation* (V&V) in complex systems and social simulation where multiple autonomous adaptive agents interact with each other. This is because such computational systems or simulations are difficult to *verify* in terms of checking program-bugs and their outcomes are also difficult to *validate* even when there are no program-bugs. These difficulties are mainly caused by a complex interaction among agents that derives emergent phenomena in MAS and ABSS.

To address this V&V issue, computer science research has proposed several V&V methods [18,13,28,4]. However, these methods are only valid for *static systems* where a state in a system is deterministically changed like a single agent system and not for *dynamic systems* where a state is dynamically changed like multiagent systems. Social science research, on the other hand, has addressed this issue by *replicating* other models to investigate whether two computational models can produce the same results.[1] If the two results are the same, then both computational models that derive results are minimally verified and validated. For example, Axtell replicated Axelrod's *culture models* in Epstein and Axtell's *Sugarscape* [2]. Such replication also contributes to an enrichment of our understanding of simulation results. It should be noted, however, that it is not easy to replicate either computational model with the other because of the following reasons: (1) it is difficult to compare different computational models under the same evaluation criteria, because they are developed according to their own purpose; (2) common parts in different computational models are very small; and (3) simulation results are sensitive to how the agents are modeled, which makes it difficult to produce the same results. These difficulties prevent replication of computational models and their fair comparisons.

To remove these difficulties, this paper suggests comparing the results of computational models whose agents differ only in *one element.* An example of such an element includes *learning mechanisms* applied to agents. Precisely, this type of V&V is not based on the *between*-models addressed in conventional research but on a *within*-model. The importance of this type of V&V increases when addressing complex dynamics or social phenomena caused by the micro-macro loop in agent systems or societies, because simulation results are substantially affected by the difference of an element within the model.

As the first step towards V&V methods for MAS and ABSS, this paper starts by addressing a bargaining theory [15] that is familiar with both MAS and ABSS, and compares the results of computational models that differ only in the learning

[1] Including this approach, Carley summarizes the V&V methods for social simulations as follows [5]: (1) *theoretical verification* that determines whether the model is an adequate conceptualization of the real world on the basis of a set of situation experts; (2) *external validation* that determines whether or not the results from the virtual experiments match the results from the real world; and (3) *cross-model validation* that determines whether or not the results from one computational model map onto, and/or extend, the results of another model.

mechanisms applied to the agents. The employed learning mechanisms are: (1) *evolutionary strategy (ES)* [3]; (2) the *learning classifier system (LCS)* [7,11]; and (3) *reinforcement learning (RL)* [25]. Here, these kinds of research efforts may be considered evaluations of learning mechanisms rather than verification of computational models and validation of their outcomes. However, a learning mechanism is an important element of computational models for V&V because these mechanisms derive complex dynamics or social phenomena in MAS and ABSS. We also believe that a comparison of several kinds of such elements *within* a model contributes to reaching a general V&V. Therefore, we begin by investigating a comparison of computational models with different *learning mechanisms* in a multiagent-based simulation.

This paper is organized as follows. Section 2 explains one bargaining game in bargaining theory, and a concrete implementation of agents is described in Section 3. Section 4 presents computer simulations, and Section 5 discusses a comparison of the results of different computational models. Finally, our conclusions are given in Section 6.

2 Bargaining Game

As a concrete domain, we focus on *bargaining theory* [14,15] and employ a *bargaining game* [22] addressing the situation where two or more players try to reach a mutually beneficial agreement through negotiations. This game is proposed for investigating when and what kinds of offers of an individual player can be accepted by the other players. We selected this domain for the following reasons: (1) this game is familiar with both MAS and ABSS as described in Section 1; and (2) since the rational behaviors of players have already been analyzed in *game theory* [20], we can verify computational models and validate simulation results by comparing the rational behaviors of players.

To understand the bargaining game, let us give an example. Rubinstein illustrated a typical situation using the following scenario [22]: two players, P_1 and P_2, have to reach an agreement on the partition of a "pie". For this purpose, they alternate offers describing possible divisions of the pie, such as "P_1 receives x and P_2 receives $1 - x$ at time t", where x is any value in the interval [0, 1]. When a player receives an offer, the player decides whether to accept it or not. If the player accepts the offer, the negotiation process ends, and each player receives the share of the pie determined by the concluded contract. Otherwise, the receiving player makes a counter-offer, and all of the above steps are repeated until a solution is reached or the process is aborted for some external reason (*e.g.,* the number of negotiation processes is finite or one of the players leaves the process). If the negotiation process is aborted, both players can no longer receive any share of the pie.

Here, we consider the finite-horizon situation, where the maximum number of steps (`MAX_STEP`) in the game is fixed and all players know this information as common knowledge [24]. In the case where `MAX_STEP` = 1 (also known as the *ultimatum game*), player P_1 makes the only offer and P_2 can accept or refuse it. If P_2 refuses the offer, both players receive nothing. Since a rational player is based on the notion of "anything is better than nothing", a rational P_1 tends to keep most of the pie to herself by offering only a minimum share to P_2. Since there are no further steps to be played in the game, a rational P_2 inevitably accepts the tiny offer.

By applying a backward induction reasoning to the situation above, it is possible to perform simulation for `MAX_STEP` > 1. For the same reason seen in the ultimatum game, the player who can make the last offer is better positioned to receive the larger share by offering a minimum offer [24]. This is because both players know the maximum number of steps in the game as common knowledge, and therefore the player who can make the last offer can acquire a larger share with the same behavior of the ultimatum game at the last negotiation. The point of multiple steps negotiation is to investigate whether the advantageous player can keep the negotiation to the last one to acquire a larger share under the situation where each step in the negotiation process is not constrained by previous ones. From this feature of the game, the last offer is granted to the player who does not make the first offer if `MAX_STEP` is even, because each player is allowed to make at most `MAX_STEP` /2 offers. On the other hand, the last offer is granted to the same player who makes the first offer if `MAX_STEP` is odd.

After this section, we use the terms "payoff" and "agent" instead of the terms "share" and "player" for their more general meanings in the bargaining game.

3 Modeling Agents

To implement agents in the framework of the bargaining game described in the previous section, we employ the following three learning mechanisms: (1) *evolutionary strategy (ES);* (2) *learning classifier system (LCS);* and (3) *reinforcement learning (RL).* We employ these mechanisms for the following reasons: (1) the ES mechanism performs well with a real number that can represent various offer values in the bargaining game; (2) the LCS architecture is implemented by modeling human beings [11], and several conventional research works employing LCS have already investigated social problems *(e.g.,* an artificial stock market [1]); and (3) the RL mechanism is well studied in the context of computer science. Specifically, we employ (1) the conventional *$(\mu + \lambda)$ evolution strategies* [3] for ES; (2) a *Pittsburgh-style classifier system* [23] instead of a Michigan-style classifier system [10] for LCS; and (3) *Q-Learning* [27] for RL.

Here, considering the strategies (defined later) of the bargaining agents, the ES and LCS mechanisms update the *contents* of strategies (*i.e.,* offer values), while the RL mechanism updates the *worth* of strategies *(i.e.,* the worth of offer values).[2] From this difference, this section starts by describing the ES- and LCS-based agents and then describes the RL-based agents.

[2] In the context of RL, worth is called "value". We select the term "worth" instead of "value" because the term "value" is used as a numerical number that represents the offer in strategies.

3.1 ES- and LCS-Based Agents

The ES- and LCS-based agents are implemented by the following components.

- **Memory**
  - **Strategies memory** in Figure 1 stores a set of strategies (the number of strategies is n) that consist of fixed numbers of pairs of offers (O) and thresholds (T). These strategies are similar to those used in Oliver's study [19]. The offer and threshold values are encoded by floating point numbers in the interval [0, 1]. In this model, agents independently store different strategies, which are initially generated at random.
  - **Selected strategy memory** stores the one strategy selected to confront the strategy of an opponent agent. Figure 1 shows the situation where agent A_1 selects the $x\text{th}$ strategy while agent A_2 selects the $y\text{th}$ strategy.
- **Mechanism**
  - **Learning mechanism** updates both offer and threshold values in order to generate good strategies that acquire a large payoff. The detailed mechanism is described later.

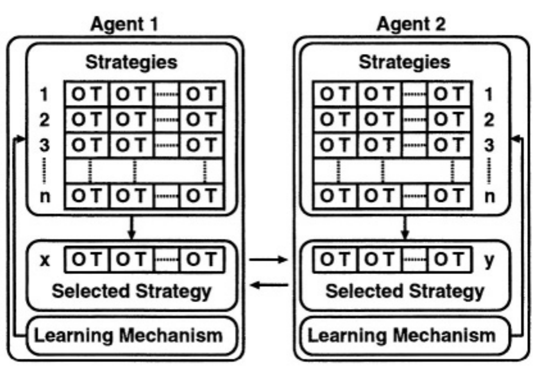

Fig. 1. ES- and LCS-based agents

As a concrete negotiation process, agents proceed as follows. Defining $\{O,T\}_i^{A\{1,2\}}$ as the $i\text{th}$ offer or threshold value of agent A_1 or A_2, agent A_1 starts with the first offer $O_1^{A_1}$. Here, we count one *step* when either agent makes an offer. Then, A_2 accepts the offer if $O_1^{A_1} \geq T_1^{A_2}$; otherwise, it makes a counter-offer $O_2^{A_2}$, *i.e.,* the offer of A_2. This cycle is continued until either agent accepts the offer of the other agent or the maximum number of steps (MAX_STEP) is exceeded. To understand this situation, let us consider the simple example where MAX_STEP= 10, as shown in Figure 2. Following this example, A_1 starts by offering 0.1 to A_2. However, A_2 cannot accept the first offer because it does not satisfy the inequality of $O_1^{A_1}(0.1) \geq T_1^{A_2}(0.9)$. Then, A_2 makes a counter-offer 0.1 to A_1. Since A_1 cannot accept the second offer from A_2 for the same reason, this cycle is continued until A_1 accepts the 10th offer from A_2, where the offer satisfies the inequality of $O_{10}^{A_2}(0.1) \geq T_{10}^{A_1}(0.1)$. If the negotiation fails, which means that the maximum number of steps has been exceeded, both agents can no longer receive any payoff, *i.e.,* they receive 0 payoff. Here, we count one *confrontation* when the above negotiation process ends or fails.

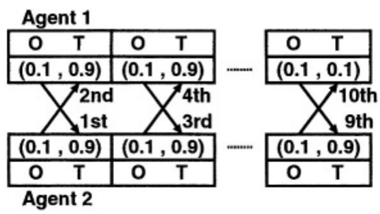

Fig. 2. Example of a negotiation process (ES- and LCS-based agents)

Next, the fitness of each strategy is calculated by the average of payoffs acquired in a fixed number of confrontations (CONFRONTATION), where the strategies of the other agents are randomly selected in each confrontation. For example, the $x\text{th}$ strategy of A_1 in Figure 1 confronts the randomly selected strategies of the other agents in the CONFRONTATION number of confrontations, and then the fitness of the $x\text{th}$ strategy is calculated by the average of the payoffs acquired in these confrontations. Since each agent has n number of strategies, the $(\texttt{CONFRONTATION} \times n \times 2)$ number of confrontations is required to calculate the fitness of all strategies of the two agents. Here, we count one *iteration* when the fitness of all the strategies of the two agents is calculated.

In each iteration, the EC- and LCS-based agents update their own strategies by modifying the numerical values of the offer and threshold by the following conventional *elite selection* procedure [7]: (1) a fixed number (μ or $\texttt{GENERATION\_GAP} \times n$) of the best strategies (*parents, i.e.,* strategies with high fitness values) remains in the set; (2) a fixed number (λ or $\texttt{GENERATION\_GAP}\times n$) of new strategies *(offspring)* is produced from the set of parents by applying the mutation operation in $(\mu + \lambda)$-ES and the crossover, mutation, and inversion operations in the Pittsburgh-style LCS; and (3) new strategies replace the same number of strategies with low fitness values. Note that this way of updating the strategies of agents does not mean to simply apply the evolutionary operations such as crossover, mutation, and inversion to the entire population of strategies, but to apply them to newly generated populations to maintain elite strategies.

3.2 RL-Based Agents

Next, the RL-based agents are implemented by the following components.

- **Memory**
  - **Strategies memory** stores a fixed number of matrixes of offers (O) and thresholds (T) as shown in Figure 3. The RL-based agents have

these matrixes because they do not have a mechanism for updating the *contents* of strategies *(i.e.,* offer and threshold values) like the ES- and LCS-based agents, but have a mechanism for updating the *worth* (Q) of strategies (precisely, the worth of pairs of offer and threshold). In this model, agents independently have different worths of strategies through learning.

- **Combined strategy memory** creates and stores one strategy by combining several pairs of offer and threshold, where each of the pairs is derived from each matrix as shown in Figure 3. Based on this strategy, an agent confronts the strategy of the other agent.

– **Mechanism**

- **Learning mechanism** updates the worth of pairs of offer and threshold in order to generate good strategies that acquire a large payoff. The detailed mechanism, except for the action selection *(acceptance or counter-offer),* is described later. The action selection of RL in this paper is based on the *ϵ-greedy method,* which selects an action of the maximum worth (Q-value) at the $1-\epsilon$ probability, while selecting an action randomly at the $\epsilon (0 \leq \epsilon \leq 1)$ probability.

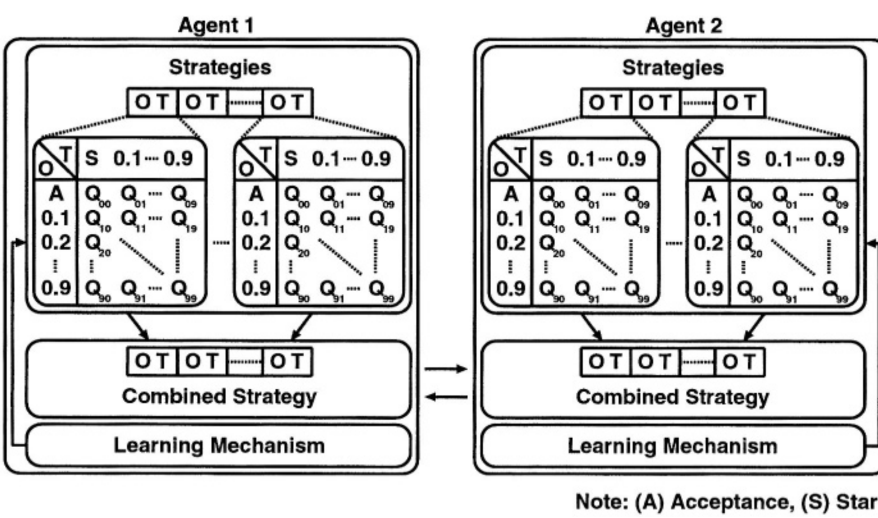

Fig. 3. RL-based agents

As a concrete negotiation process, agents proceed as follows. Defining $\{O,T\}_i^{A\{1,2\}}$ as the ith offer or threshold value of agent A_1 or A_2 as the same as ES- and LCS-based agents, agent A_1 starts with the first offer $O_1^{A_1}$. Then, A_2 accepts the offer if the acceptance (A) in the row $T_2^{A_2}(= O_1^{A_1})$ of a matrix is selected; otherwise, it makes a counter-offer $O_2^{A_2}$ determined from the same row

$T_2^{A_2}(=O_1^{A_1})$. This cycle is continued until either agent accepts the offer of the other agent or the maximum number of steps (MAX_STEP) is exceeded. To understand this situation, let us consider the simple example where MAX_STEP = 10, as shown in Figure 4. Following this example, A_1 starts to make an offer $O_1^{A_1}(0.1)$ to A_2 by selecting one value in the row $T_1^{A_1}$ *(S(start))*. However, A_2 does not accept the first offer, because it decides to make an $O_2^{A_2}(0.1)$ counter-offer selected from a value in the row $T_2^{A_2}(0.1)$. In this example, the cycle is continued until A_1 accepts the 10th offer from A_2 by selecting $O_{10}^{A_1}$ *(A(acceptance))* selected from a value in the row $T_{10}^{A_1}(0.1)$. If the negotiation fails, which means that the maximum number of steps has been exceeded, both agents can no longer receive any payoff, *i.e.,* they receive 0 payoff. Here, as in case of the ES- and LCS-based agents, we count one *confrontation* when the above negotiation process ends or fails.

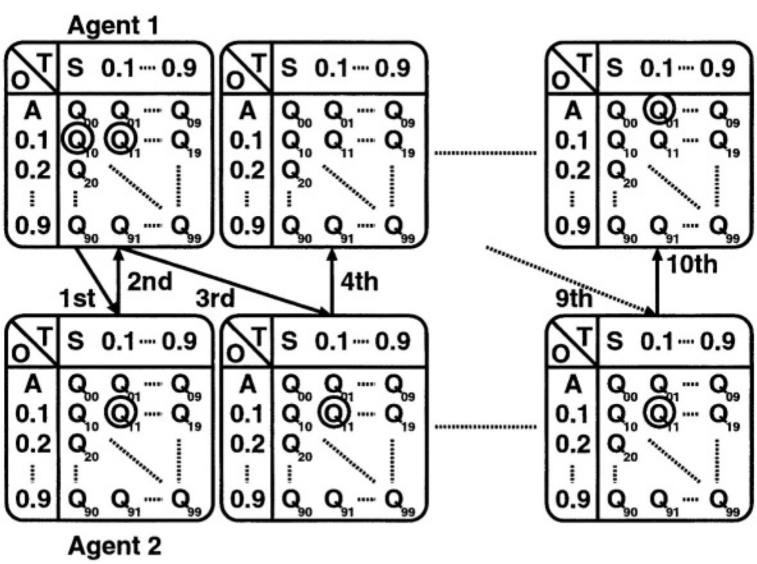

Fig. 4. Example of a negotiation process (RL-based agents)

In each confrontation, the RL-based agents update the worth pairs of offer and threshold by the following conventional equation (1), where $Q(t,o)$, $Q(t',o')$, r, $O(t')$, $\alpha(0 < \alpha \leq 1)$, and $\gamma(0 \leq \gamma \leq 1)$, respectively, indicate the worth of selecting the offer (o) at threshold (t), the worth of selecting the 1 step next offer (o') at the 1 step next threshold (t'), the reward corresponding to the acquired payoffs, a set of possible offers at the 1 step next threshold (t'), the learning rate, and the discount rate.

$$Q(t,o) = Q(t,o) + \alpha[r + \gamma \max_{o' \in O(t')} Q(t',o') - Q(t,o)] \tag{1}$$

Finally, we count one *iteration* when the ($\texttt{CONFRONTATION} \times n \times 2$) number of confrontations is done, in order to investigate the simulation results of the RL-based agents at the same level of the ES- and LCS-based agents. Note that CONFRONTATION (*i.e.,* the number of confrontations for each strategy) and n (*i.e.,* the number of strategies) are determined in the simulation of the ES- and LCS-based agents.

4 Simulation

4.1 Simulation Design

The following two simulations are conducted as comparative simulations.

- **ES vs. LCS:** Investigation of the influence of different learning mechanisms handling *continuous* values for representing strategies. In detail, both offer and threshold values in this case are represented by ordinal real numbers (*e.g.,* 0.11, 0.234, or 0.9117).
- **ES vs. RL:** Investigation of the influence of different learning mechanisms handling *discrete* values for representing strategies. In detail, both offer and threshold values in this case are restricted by a real number with one decimal digit (*e.g.,* 0.1, 0.2, or 0.9) in ES, while they are represented by the discrete values in a 0.1 unit in RL as shown in Figure 3.

In each simulation, the following two cases are investigated. Note that all simulations are conduced up to 5000 iterations, and their results show average values over 10 runs.

- **Case (a):** Payoff
- **Case (b):** Average negotiation process size

As the parameter setting, the variables are set as shown in Table 1. Note that preliminary examinations found that the tendency of the results does not drastically change according to the parameter setting.

4.2 Simulation Results

Figure 5 shows the simulation results of both the ES and LCS. In detail, the upper figures indicate the payoff, while the lower figures indicate the average negotiation process size. The vertical axis in the figures indicates these two cases, while the horizontal axis indicates the iterations. In particular, the payoff of agent A_1 is shown in the lower lines, while that of A_2 is shown in the upper lines. Furthermore, Figure 6 shows the simulation results of the ES restricted to a real number with one decimal digit and RL. All axes in this figure have the same meaning as those in Figure 5. From these results, we find that the difference tendency follows the different learning mechanisms applied to the agents.

Table 1. Parameters in simulations

Common parameters for bargaining game		
MAX_STEP	the maximum number of steps in one confrontation	10
ES parameters		
n	the number of strategies	50
CONFRONTATION	the number of confrontations for each strategy	20
μ	the parent population size	25
λ	the offspring population size	25
σ	the initial standard deviation of a Gaussian distribution	0.5
LCS parameters		
n	the number of strategies	50
CONFRONTATION	the number of confrontations for each strategy	20
GENERATION_GAP	the percentage of replaced strategies	50%
CROSSOVER_RATE	the percentage of crossover operations	100%
MUTATION_RATE	the percentage of mutation operations	5%
INVERSION_RATE	the percentage of inversion operations	5%
RL parameters		
α	the learning rate	0.1
γ	the discount rate	1.0
ϵ	the ϵ-greedy method	0.05

5 Discussion

5.1 ES vs. LCS

First, we conduct simulations on different learning mechanisms that handle *continuous* values for representing the strategies shown in Figure 5. This figure shows that (1) the payoff of the ES-based agents finally converges at the almost maximum or minimum value *(i.e.,* 100% or 0%), while that of the LCS-based agents neither converges at a certain value nor close to the maximum or minimum value; and (2) the average negotiation size of the ES-based agents increases,[3] while that of the LCS-based agents does not but simply oscillates.

The reasons for the above results are summarized as follows: (1) the values added to or subtracted from the offer and threshold values in ES decrease as the iterations become large, while the crossover, mutation, and inversion operations in LCS are constantly performed. Since most of these operations work as a divergent or explored factor, the decrease of this influence makes simulation results converge; otherwise, it derives an instability of the simulation results; (2)

[3] The value after 5000 iterations is finally converged at near 10.

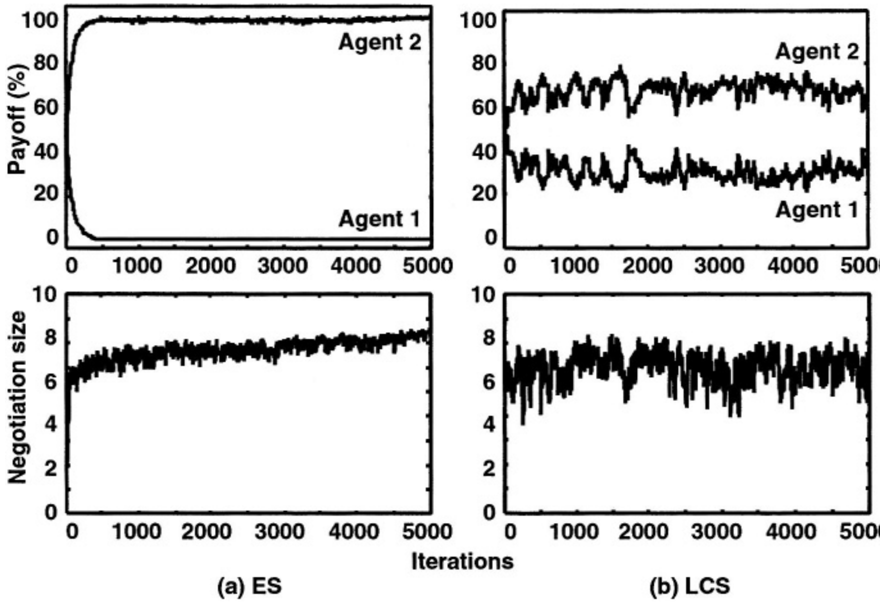

Fig. 5. Simulation results of ES vs. LCS: Average values over 10 runs at 5000 iterations

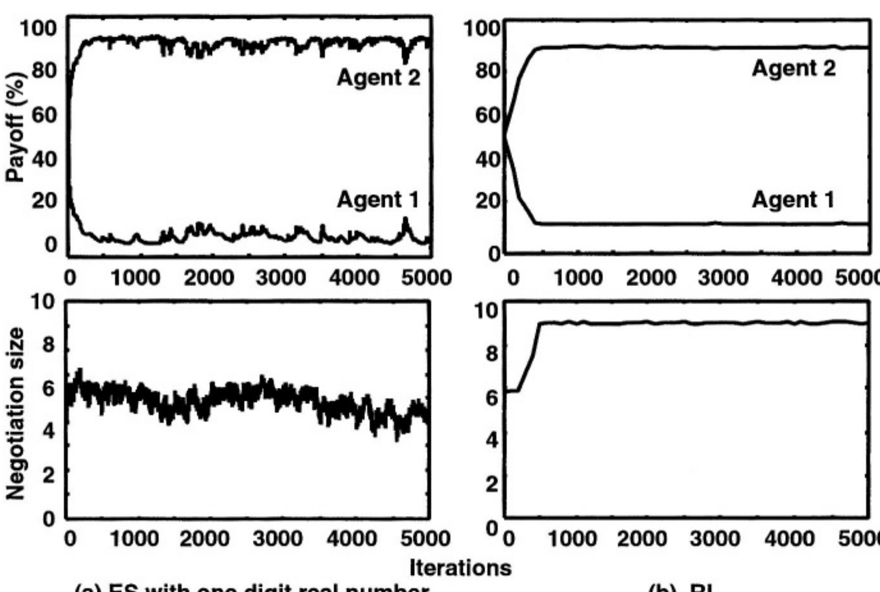

Fig. 6. Simulation results of ES with one decimal digit vs. RL: Average values over 10 runs at 5000 iterations

the offer and threshold values in all offspring are modified at every iteration in ES, while they are modified only by a mutation operation executed at a low probability in LCS. Furthermore, ES modifies such values in the manner of a gradient search, while LCS modifies them randomly.

Here, we consider that game theory proves that rational agents A_1 and A_2 receive the maximum and minimum payoffs in the final negotiation process, respectively. This is because A_1 in our simulations has to accept any small offer proposed by A_2 at the 10th negotiation process; otherwise, A_1 cannot receive any payoff, *i.e.,* it receives 0 payoff. Therefore, we expect the following simulation results: (1) learning agents can acquire the maximum and minimum payoffs; and (2) the average negotiation size increases if the agents learn strategies appropriately. In analyzing the simulation results according to the above two assumptions, the ES-based agents show the same tendency in game theory, but the LCS-based agents do not. Note that "the same tendency" means to show similar results given by game theory.

5.2 ES vs. RL

Next, we investigate the simulation results on different learning mechanisms handling *discrete* values for representing strategies as shown in Figure 6. This figure shows that (1) the payoff in the ES restricted to a real number with one decimal digit does not completely converge, while that in the RL finally converges at a value near to the maximum or minimum value (*i.e.,* 90% or 10%); and (2) the average negotiation size in the restricted ES decreases, while that in the RL increases.

As for the first result on the payoff, the payoff by RL does *not* converge at the almost maximum or minimum value (*i.e.,* 100% or 0%), because the action selection of the RL in this simulation is based on the ϵ-**greedy** method, which means that agents behave randomly at some percentage *(i.e.,* the 0.05% in this simulation). Such random actions prevent an acquisition of rational behaviors that derive mostly a maximum or minimum payoff. In this sense, it seems that the restricted ES slightly outperforms the RL only from the viewpoint of the convergent values, but we would here claim that both values are mostly the same, and this difference can be reduced by minimizing the ϵ value. Therefore, we do not discuss this difference in detail.

As for the second result on the negotiation size, the negotiation size in RL increases while that in the restricted ES decreases.[4] We can understand this result by focusing on the 10th offer in Figure 2, where the values of the offer and threshold are set as 0.11 and 0.12, respectively. In this case, the agent who receives the offer from the opponent agent cannot accept it in the normal ES because the inequality of $O(0.11) \geq T(0.12)$ described in Section 3.1 is not satisfied. In contrast, the same agent accepts the offer in the ES restricted to a

[4] Note that the negotiation size in RL does *not* converge at the almost maximum value (*i.e.* 10) but converge at 9 due to the randomness from the ϵ-**greedy** method as mentioned above.

real number with one decimal digit because the inequality of $O(0.1) \geq T(0.1)$ is satisfied. In RL, on the other hand, the same agents can learn to refuse the offer from the opponent agent, even though their strategies are represented by the discrete values in the 0.1 unit (not in the 0.01 unit). This is because the decision of acceptance or rejection of the offer in RL is determined not by values of offer and threshold but by the probabilities of their worth. This means that such a decision is not affected by a restriction on the explanation of values in strategies. Here, the above analysis is based on an example of the 10th offer in Figure 2, but the same holds for other steps. For this reason, agents with the restricted ES may accept unwilling (*i.e.,* small) offers in each negotiation process size, while the normal ES or RL can learn not to accept them.

These findings indicate that (1) the restricted ES-based agents cannot show the same tendency in game theory, even through the normal ES-based agents can; and (2) in comparison with the restricted ES-based agents, the RL-based agents can show the same tendency in game theory, even though their strategies are represented by the 0.1 discrete unit. Note that the V&V based on engineering science investigates how an influence of knowledge representation in systems *(i.e.,* strategies of agents in this model) can be reduced, while the V&V based on social science investigates sensitivity of knowledge representation by checking whether simulation results of different knowledge representation produce the same or not.

5.3 Implications and V&V

The above analysis suggests that learning mechanisms that enable agents to acquire their rational behaviors differ according to the knowledge representation (*i.e.,* strategies in the bargaining game) of the agents. In particular, the ES mechanism can elicit rational behaviors of agents when strategies are represented by continuous values such as an ordinal real number, while the RL mechanism can elicit the same behaviors when strategies are represented by discrete values. From these implications, we learned the following important lessons: (1) an investigation of the feature of the learning mechanisms is indispensable to determine appropriate learning mechanisms when applying to MAS; and (2) the same investigation should be done before investigating the social problems in ABSS because simulation results are sensitive to the learning mechanisms.

Although the above lessons are very important for MAS and ABSS, it should be noted that these lessons are based on both verification of computational models and validation of simulation results. In this research, however, computational models and simulation results were neither verified nor validated by simply comparing both results. This is because two compared results are different from each other. However, using a comparison of results in game theory verifies and validates computational models and simulation results, respectively, in the case of ES- and RL-based agents. Note that the simulation results of ES-based agents employing discrete values differ from those in game theory, but the same ES-based agents are verified and validated when employing continuous values (The only difference is strategy representation in the bargaining game). LCS-based agents were neither verified nor validated in this research, but they are verified and validated in the other experiments.

From this discussion, computational models and their results are verified and validated from the viewpoint of *rational behaviors* of agents analyzed in the bargaining game. What should be noted here is that this type of V&V is based on *rationality,* which is one aspect of V&V. Another example includes V&V from the viewpoint of *human-based behaviors,* which aspect is quite important in ABSS. This indicates that LCS-based agents may be verified and validated in terms of *humanity* because the results of LCS-based agents are similar to human actors analyzed in *experimental economics* [17,9,16,21]. Since such an implication was obtained even though human actors and LCS-based agents conduct the same example independently, it is important to explore V&V methods from several viewpoints towards a general V&V that covers a lot of aspects including rationality, humanity, and etc. However, results obtained in this paper indicate that (1) *rationality*-based V&V shows a potential of verifying computational models and validating their results; and (2) rationality focused on in our V&V can be shared as a common aspect in both MAS and ABSS, because MAS is mainly based on rationality and not on humanity while the ABSS also regards rationality as an important aspect like in the game theory.

5.4 Future Directions

In addition to the future research described in the previous section, the following endeavors should be pursued:

- **Relationship between examples and elements of computational models:** One of the most significant directions is to investigate the relationship between examples (*e.g.,* the bargaining game) to be used and elements of computational models (*e.g.,* the learning mechanism) to be tested. Such comprehensive investigations, including many simulations in other domains and other elements, would contribute to exploring the V&V methods for MAS and ABSS.
- **Complex simulation:** Another direction is to conduct complex simulation. For example, a comparison of simulation results with more than two agents is indispensable because this research only employs two players which means an actually minimal multiagent-based simulation. As another example, investigations of other types of negotiation (*e.g.,* synchronous/asynchronous negotiation or negotiation with mixed strategies including continuous and discrete ones) are also required to verify computational models and validate simulation results in complex cases.
- **A link to the real world:** As mentioned in the previous section, it is significant to link simulation results to the real world though a comparison with observed behavioral patterns of human players and their variability. In particular, rational behaviors analyzed in game theory are not those of real actors analyzed in *experimental economics* [6,12] or *gaming simulations* [8].

From this fact, it is important to link not only to game theory but also to the real world towards enhanced V&V methods.[5]

6 Conclusions

This paper compared several computational models with different *learning mechanisms* in a bargaining game and analyzed the outcomes of those models to verify computational models and validate simulation results. Specifically, we made the following two comparisons towards V&V: (a) ES- vs. LCS-based agents, both handling *continuous* knowledge representation of agents; and (b) ES- vs. RL-based agents, both handling *discrete* knowledge representation. Through our comparisons of the above simulations, we found that (1) computational models and simulation results are minimally verified and validated in the case of ES- and RL-based agents; and (2) learning mechanisms that enable agents to acquire their rational behaviors differ according to the knowledge representation of the agents.

However, these results have only been obtained from three learning mechanisms (*i.e.,* ES, LCS, and RL) and from one social problem (*i.e.,* the bargaining game). Therefore, further careful qualifications and justifications, such as analyses of results using other learning mechanisms or in other domains, are needed to improve the V&V methods for MAS and ABSS. Such important directions must be pursued in the near future in addition to the future direction described in Section 5.4. However, addressing common issues in both MAS and ABSS contributes not only to bridging the gap between two different research areas but also to supporting each other by providing their own approaches.

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[5] One such direction will be reported in [26].

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Weak Interaction and Strong Interaction in Agent Based Simulations

Fabien Michel, Abdelkader Gouaïch, and Jacques Ferber

LIRMM Laboratoire d'Informatique, Robotique et Micro-électronique de Montpellier.
C.N.R.S. – Université Montpellier II, 161 rue Ada 34392 Montpellier Cedex 5 - France
{fmichel, gouaich, ferber}@lirmm.fr
http://www.lirmm.fr/~{fmichel, gouaich, ferber}

Abstract. This paper addresses the problem of the *engineering divergence phenomenon* in ABS. This problem is related to the fact that a particular conceptual model may give different outputs according to its implementation. Through two experiments, the paper shows that the implementation of the agents' interaction is one of the factors that are involved in this phenomenon. The underlying idea of this paper is that this problem can be greatly diminished if the analysis of the conceptual model incorporates some key concepts which are crucial for the implementation. To this end, this work proposes to identify two different classes of interaction: *weak interactions* and *strong interactions*.

1 Introduction

Agent Based Simulations (ABS) constitute an experimental tool of choice. Agent Based Modelling allows to directly represent the individuals, their behaviours and their interactions [1]. Each individual is named an *agent* and is supposed to represent an autonomous, proactive and social entity [2]. The autonomy relies on the fact that agents have full control of their behaviours. Unlike passive objects, agents proactively perform actions in their environment. In the scope of this paper, the social feature is defined as the ability of an agent to interact with others. Thus ABS are widely used to explore and design complex decentralised systems such as ant colonies, autonomous robots, social systems and so on.

As for any computer simulation [3], the ABS engineering schema can be described as follows:

1. Model design: during this phase, the simulation is expressed in a conceptual model (CM for short) that specifies the characteristics of the simulated system.
2. Model execution: during this phase, the CM specifications are implemented in concrete computational structures and programs that constitute the *simulator* of the experiment.
3. Execution analysis: during this phase, the outputs of the simulation are checked according to some validation rules and then interpreted.

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Regarding this engineering process, a fundamental issue is raised using ABS: there is no consensus about the specifications that must be given to a CM (e.g. [4]). Thus, starting from a single CM and following this engineering process, several *computational models* (implementations) can be elaborated. Consequently, very different outputs may be obtained and the question of ABS experiments' reliability must be raised. Recent works such as [5,6] clearly address this matter. In this paper, this problem is identified as the *engineering divergence phenomenon.* It is important to distinguish this phenomenon, observed at the engineering phases, from the divergence of a particular CM due to its inherent properties. For instance, a chaotic system diverges, for each execution, using the same programming environment. This paper addresses the problem of the divergence of the outputs when different expertises and technologies are involved.

This paper focuses on the management of the agents' interactions and proposes to classify them along two different classes: *weak interactions* and *strong interactions.* The paper argues that simulations do not require the same programming technology according to the nature of the interactions present in the model. Thus, this distinction enables to refine the CM and diminish the engineering divergence phenomenon by reducing the possible implementations of the CM. This paper is structured as follows: Sect. 2 introduces the *engineering divergence problem* and describes the aims of the paper. The next section details the analysis of two experiments which are based on a minimalist CM. Section 4 discusses the results and proposes key concepts for refining a CM. The conclusion of this paper summarises the hypothesis and proposals of the paper.

2 The Engineering Divergence Phenomenon

2.1 Principle of ABS

Let us assume that Σ defines the whole possible states of the studied system, every ABS is based on the assumption that the environment evolution from one moment t to the next $t+dt$ results from the composition of the actions, $A_1(t), A_2(t)...A_n(t)$, produced by the agents and of the environment's action produced by its natural evolution, $E_n(t)$, at t. In a simplified way, the problem is to build a time function, *Dynamic* $D : \Sigma \mapsto \Sigma$, such as:

$$\sigma(t + dt) = D(\uplus(A_n(t), E_n(t)), \sigma(t)) \; . \tag{1}$$

The symbol $\uplus$ is used here to denote the action composition operator. It defines how the actions produced at the instant t must be composed in order to calculate their consequences on the previous world state $\sigma(t)$. Without detailing this calculus, it is easy to measure the difficulty of conceptualising such an operation knowing the diversity and the nature of the concepts hidden behind the word action: movement, decision-making, environment modification, and so on.

2.2 Technical Structure of ABS Platforms

Since the ABS area of appliance is not restricted to a particular research field, ABS software applications do not follow particular development rules. Thus they are very heterogeneous regarding the way of using them, the nature of the models they consider and their internal computational structures and components. However, from a technical point of view they always incorporate, explicitly or not, at least three core components that we identify as follows (Fig. 1):

– The *behaviour module:* this module defines behaviours of the simulated entities in concrete computational structures.
– The *scheduler module:* it defines the manner in which the agents are executed during the simulation, namely the activation structure.
– The *interaction management module:* this module defines how the interactions among the entities are handled.

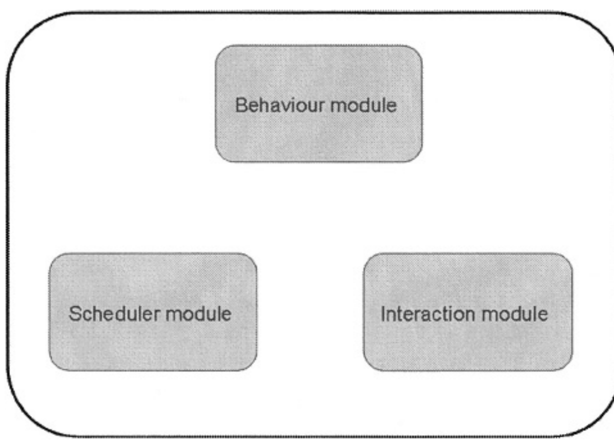

Fig. 1. The three core components of ABS platforms

2.3 Divergence of Simulation Outputs

As said in Sect. 1, if the specifications of the simulation CM are incomplete, the CM can be implemented in several ways and thus can yield different outputs. For instance, if the CM does not define clearly the model's time evolution, it is possible to implement it using a synchronous or an asynchronous simulation technique. Problems related to this particular point have been clearly shown and studied in works such as [7,8,9,10]. These works mainly focus on how the implementation of the scheduler module influences the outputs. For instance, [8] shows that *The Sugarscape Model*[1] (an adaptation of the model used in [11]) does

[1] *The Sugarscape Model* consists in a spatial distribution of generalised resource that agents need where agents have the ability to reproduce themselves.

not produce the same outputs for two different implementations. The authors explain that this divergence is due to the techniques used to schedule the execution of the agents' actions, namely the *activation structure* i.e. whether actions are performed synchronously or asynchronously[2]. Such a correlation between activation structures and outputs is also made is the previous cited works. Specifying the characteristic of the *scheduler module* in the CM, according to the nature of the studied system, is an important step that has improved the practical realisation of ABS by reducing the engineering divergence phenomenon related to this module.

As a matter of facts, the two other modules can also contribute to engineering divergence phenomena. Indeed, as shown in the next section, the implementation of the *interaction module* may also deeply influence the simulation outputs, even if the activation structure remains unchanged. Thus the work presented in this paper aims to:

- show that the interaction module is a key feature in the ABS framework.
- show that ABS involve different kinds of interaction that do not require the same programming attention.
- introduce some key concepts which can be used to refine the CM by specifying the nature of the interactions and thus the way they have to be implemented.

3 Experiments

3.1 Experimental Protocol

This section presents two experiments. The first deals with the modelling of the reproduction behaviour. The second consists in modelling resource consumption behaviours. The experiments are carried out using a testing platform defined by three modules as described in Sect. 2.2. As said in Sect. 2.3, the engineering divergence phenomenon may rely on the implementation of these three modules. Thus each module may potentially modify the outputs of the simulation. However, in this paper, the experimental protocol used for the two experiments presented here consists in building simulations where only the *interaction management module* is modified. Doing so will clearly identify the influence of this specific module on the obtained outputs.

3.2 Experiment 1: Reproduction Behaviour

In this section, a CM of reproduction behaviours is studied. The corresponding CM is defined as follows: let us consider two compatible (fertile and of the opposite sex) autonomous agents, A and B, with a simple behaviour which is only a choice between two actions: reproduce ($Agent_{repro}$) or do nothing ($Agent_{none}$) according to a defined probability $Pr(Agent_{behaviour})$.

[2] Specifically, the authors were interested in finding a suitable activation structure to simulate artificial societies.

Behaviour Module. For this CM, the behaviour module is defined as follows:

Table 1. The behaviour of agents as probabilities

$Pr(A_{repro}) = \alpha$ and $Pr(A_{none}) = 1 - \alpha$
$Pr(B_{repro}) = \beta$ and $Pr(B_{none}) = 1 - \beta$

Scheduler Module. The chosen activation structure consists in a discrete time simulation used with a classic synchronous time evolution. This method consists in activating all the agents in a sequential way and then incrementing the time of the simulation by one time unit. Moreover, we have randomized the activation list to avoid a possible advantage of one agent as proposed by [7]. As the agents are autonomous, their behaviours are independent, which means that $A_{behaviour}$ is not correlated to $B_{behaviour}$. Thus, for each step of the simulation, there are four possible interaction situations which have to be handled by the interaction module.

Table 2. Probabilities of interaction situations

$Pr(A_{repro}$ and $B_{repro})$	$= Pr(A_{repro}) \times Pr(B_{repro})$	$= \alpha\beta$
$Pr(A_{repro}$ and $B_{none})$	$= Pr(A_{repro}) \times Pr(B_{none})$	$= \alpha - \alpha\beta$
$Pr(A_{none}$ and $B_{repro})$	$= Pr(A_{none}) \times Pr(B_{repro})$	$= \beta - \alpha\beta$
$Pr(A_{none}$ and $B_{none})$	$= Pr(A_{none}) \times Pr(B_{none})$	$= 1 - \beta - \alpha + \alpha\beta$

Interaction Management Modules. These modules, the core part of the experiment, are defined according to three different ways for managing the interactions between agents. The first technique is inspired by the method used in [11]: in this case, the agents' actions are treated sequentially and each agent can reproduce, at his own turn, due to the proximity of a compatible partner. Table 3 describes the obtained results for each possible situation. The second approach for managing the agents' interactions (Table 4) corresponds to the implementation of [8]. In this case, when an agent successfully reproduce, the other agent cannot reproduce even if it has not acted yet[3]. The last interaction module is an application of the *influences / reaction* principle [12]. In this model the agents' action are considered simultaneously and we have assumed that it is necessary that the two agents want to reproduce to obtain an offspring (Table 5).

Results. Figure 2 shows the different outputs according to the three interaction management modules for hundreds of simulations: the A set of lines corresponds

[3] Lawson and Park have modified the agent reproduction rule to be more *realistic:* only one new entity can be produced by a pair of compatible agents.

Table 3. First interaction module

situations	birth(s)	probabilty
A_{repro}, B_{repro}	2	$\alpha\beta$
A_{repro}, B_{none}	1	$\alpha - \alpha\beta$
A_{none}, B_{repro}	1	$\beta - \alpha\beta$
A_{none}, B_{none}	0	$1 - \beta - \alpha + \alpha\beta$
Overall probabilities		
$Pr(births = 2) = \alpha\beta$ $Pr(birth = 1) = \alpha + \beta - 2\alpha\beta$ $Pr(birth = 0) = 1 - \beta - \alpha + \alpha\beta$		

Table 4. Second interaction module

situations	birth(s)	probability
A_{repro}, B_{repro}	1	$\alpha\beta$
A_{repro}, B_{none}	1	$\alpha - \alpha\beta$
A_{none}, B_{repro}	1	$\beta - \alpha\beta$
A_{none}, B_{none}	0	$1 - \beta - \alpha + \alpha\beta$
Overall probabilities		
$Pr(birth = 1) = \alpha + \beta - \alpha\beta$ $Pr(birth = 0) = 1 - \beta - \alpha + \alpha\beta$		

Table 5. Third interaction module

situations	birth(s)	probabilty
A_{repro}, B_{repro}	1	$\alpha\beta$
A_{repro}, B_{none}	0	$\alpha - \alpha\beta$
A_{none}, B_{repro}	0	$\beta - \alpha\beta$
A_{none}, B_{none}	0	$1 - \beta - \alpha + \alpha\beta$
Overall probabilities		
$Pr(birth = 1) = \alpha\beta$ $Pr(birth = 0) = 1 - \alpha\beta$		

to the application of the first method, the B set to the second and the C set to the third. This figure clearly shows the engineering divergence phenomenon related to the management of agents' interactions: even if the behaviour and scheduler modules remain unchanged, the outputs obtained by each method diverge. Thus, if the management of the interactions among the entities is not specified the implementation of this model can lead to an EDP.

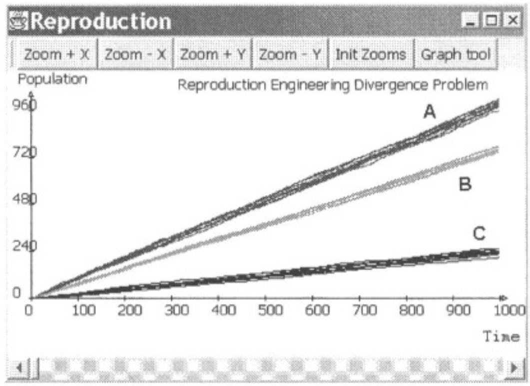

Fig. 2. Simulation outputs of the three interaction modules used in the first experiment with $\alpha = 0.4$ and $\beta = 0.6$

3.3 Experiment 2: Resource Consumption

The objective of this experiment is to study the consumption of a single resource by two agents A and B. Each agent has a life level L ($0 <= L <= max\_life\_level$) that he must maintain above a particular threshold $T(0 < T < 100)$ by consuming a resource up to the *max_life_level*. Thus the agents can exhibit two behaviours: consuming or doing nothing; $Agent_{consume}$ and $Agent_{none}$. When the life level of an agent decreases to zero the simulation is stopped. Besides the resource grows back at a rate of α units per time interval up to a defined capacity. The key statistical output of this model is a measure of the agents' average life level.

Behaviour Module. The behaviour module of the CM is defined as follows:

Algorithm 3.1: $Agent_{Behaviour}()$

if $life\_level < threshold$
  then $consume\ resource : Agent_{consume}$
  else $do\ nothing : Agent_{none}$

Scheduler Module. The scheduler module used here is exactly the same as in the previous experiment. Thus there are four situations that have to be handled by the interaction module:

Interaction Management Modules. Two different management modules have been used. The first method for managing the interactions is to immediately execute the agent's action. Hence the interactions between the resource

Table 6. Interaction situations

$A_{consume}$	and	$B_{consume}$
$A_{consume}$	and	B_{none}
A_{none}	and	$B_{consume}$
A_{none}	and	B_{none}

and one agent are reduced to two situations: the agent consumes the available resource to recover life points or the agent does not interact with the resource.

The second approach for managing the agents' interactions with the resource is to consider that actions can occur simultaneously. For instance both agents can access the resource at the same time. In this case the resource is equitably shared between the agents.

Results. Figure 3 shows the average of the outputs obtained for thousands of simulations with different initial values (T and α). These results show the outputs are similar in average and do not depend on the initial parameters (notably the abundance or scarcity of the resource, according to the α parameter) nor on the interaction module type. These results show that whatever the interaction module used and initial parameters, the results are similar in average. So even if the second method seems more advanced than the first one (because it handles simultaneity), the engineering divergence phenomenon is not observed considering this simulation model. In fact, the interaction management module has not influenced the outputs of this simulation at all.

3.4 Discussion

The first experiment clearly shows the great influence of the interaction management on the simulation outputs. Thus it stresses that it is fundamental to include the specification of the *interaction management module* in a CM for avoiding engineering divergence phenomena. However, on the basis of the two experiments, a question must be raised: why does the interaction management module influence the outputs of the first experiment while having no consequences on the second experiment?

The underlying idea of this paper is that these two experiments involve interaction processes which are very different in nature. And the paper argues that they do not require the same programming solutions for being implemented correctly (see [13] for other recent works which are related to this idea). Here, the question is to make the interaction management consistent with the meaning of the model. It is not a question of checking if the simulation's results model the reality but to know if the simulation process truly represents the model's reality that we have in mind.

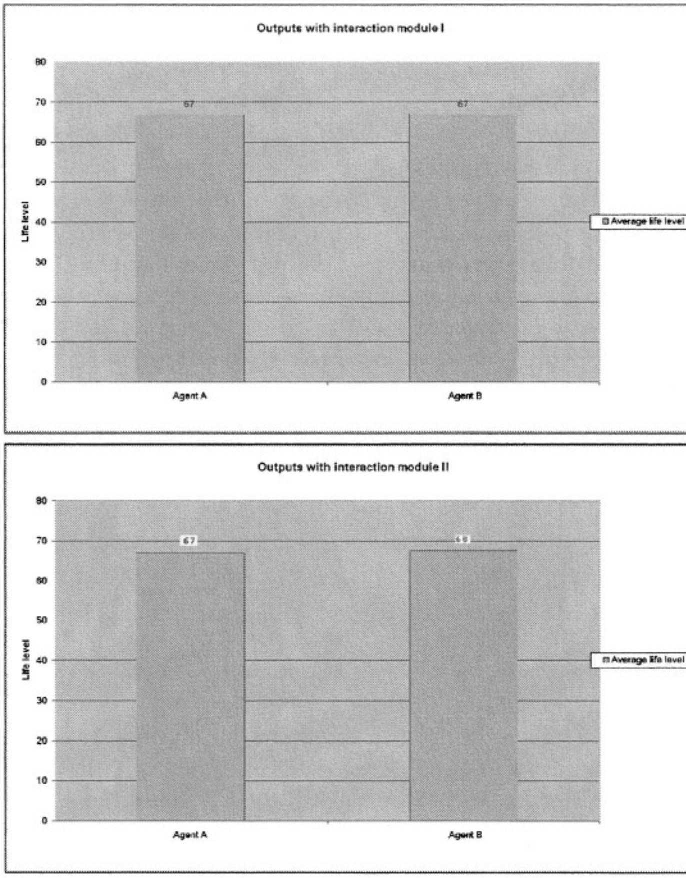

Fig. 3. Agents' average life level with first and second interaction modules

4 Weak and Strong Interactions

4.1 Strong Interaction

Let us analyse the three different implementations used in the first experiment (Sect. 3.2). With the first interaction module, where the agents' actions are treated sequentially, the results are quite surprising. Indeed, as Epstein and Axtell have noticed for their own experiments [11], one single agent can reproduce himself several times per turn. If three agents are present, the first agent produces a new entity, and then the second and the third may do the same thing[4]. So, it is obvious that, for our experiment, this first implementation of the interaction module does not agree with the meaning of the model.

[4] Epstein and Axtell say on this matter that this does happen *rarely* as an agent has a health parameter that decreases with a new birth.

It is undoubtedly the reason why [8] added a gestation period so that an agent cannot reproduce himself twice. However, this programming technique is still criticisable. The selected partner does not have any choice: the initiator has decided for both! The partner's individual behaviour, **its own goals** are not taken into account. What would happen if this agent was moving for a critical reason and found itself involved in a reproduction process that freezes its movement? This would totally contradict basic foundations of multiagent systems where agents are autonomous and not under the control of another one [2]. Indeed, when an agent modifies, directly by changing the internal state of another agent (the boolean value *pregnant* is now true), or indirectly by ordering the other agent to do it ("you are now pregnant"), the autonomy of the agent is lost. Indeed, the multi-agent approach relies on taking into account each individual. Without this assumption, the system's dynamic is not representing individual entities interacting together.

That is why, to be correctly implemented (with respect to the autonomy property), the reproduction interaction **requires** to take into account each behaviour before computing the result. The third implementation of the interaction module follows this guideline and produces a birth iff both agents want to reproduce. Indeed, if we consider **autonomous** agents, each one must independently generate a reproduction behaviour to finally interact and produce a new entity:

$$Pr(birth = 1) = Pr(A_{repro} \textbf{and} B_{repro}) = Pr(A_{repro}) \times Pr(B_{repro}) = \alpha\beta \ . \quad (2)$$

In the first experiment, a reproduction attempt has only a meaning when another agent is close. The result of such an interaction, a birth, requires at least that two agents are present in the system. An agent will never reproduce itself nor try to do it if it is alone in its environment. More precisely, reproduction is a behaviour that produces a result on the environment which can be realized when two agents are mating.

Definition 1 (Strong Interaction). *Actions of agents define a strong interaction when the feasibility of each action's goal depends on the action of another agent.*

This kind of interaction process requires considering all the involved agents before computing its result. It is important to notice that it is not a problem of coordination (as defined by [14]) between agents like in [15] for instance. The question is not to know how or why the agents internally produce or coordinate their actions in order to achieve their goals, but to specify how autonomous actions (decisions) are handled by the simulator.

4.2 Weak Interaction

The second experiment involves an interaction process that is less complex than the first one. In fact, even if the agents interact through the environment by consuming the resource, they carry out actions which are not directly correlated.

Moreover, the presence of other agents in the system is not necessary for consuming the resource: the feasibility of the goal of this action is not conditioned by the action of another agent.

This does not mean that complex situations cannot arise when dealing with *weak interactions.* For instance, the consumption of the resource can happen simultaneously. However, explicitly handling this situation does not modify the true meaning of the model because of this weak relation between the agents. Indeed, the autonomy property is respected since the two autonomous behaviours are taken into account. For instance, a collision between two robots is a *weak interaction* since space can be considered as a resource that agents consume. In this case the problem is not about managing sequentially or simultaneously the movement of the agents and the question of *realism/validity* relies on the granularity of the considered actions[5] and not on the management of simultaneity.

Definition 2 (Weak Interaction). *Agent actions define a weak interaction when the feasibility of each action's goal does not depend on the action of another agent.*

A good example of this kind of interaction type can be found in the classical "termites model" [16]. In this model the world is made of a set of termites and of a set of wood chips initially equally distributed around a toroidal environment. The termites follow a set of simple rules to gather wood chips into piles. This behaviour can be summarized with the two rules that follow:

– *Rule 1: " If I do not have a wood chip, I look for one randomly. "*
– *Rule 2: " If I have got a wood chip, I look randomly for another to put it down aside"*

Figure 4 shows four successive stages of a simulation where one can see that the wood chips end up in a single pile. In this example, the set of possible actions carried out by the agents is reduced to moving, taking and deposing an object.

It can be made an interesting remark on the behaviour of these electronic termites. A termite's behaviour does not suppose or integrate the existence of the others. Indeed a termite has no representation of its kind. So, even if the termites have the same goal, they interact in a *weak interaction* mode and, whatever the interaction management used, a single pile of woodchips is always the final result of this simulation[6]. The most interesting thing is undoubtedly that the same result is obtained when only one termite is working, but this takes only a greater amount of time.

[5] It is not relevant to raise the problem of the simultaneity of a collision when the selected space scale is coarse.

[6] This is not true in the particular case where there are more termites than wood chips.

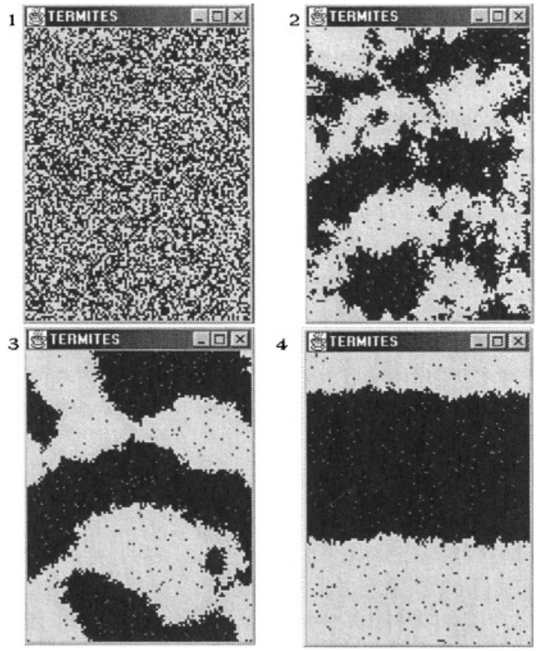

Fig. 4. The termites follow simple rules to gather wood chips into piles

4.3 Refining Conceptual Models

By classifying interactions along weak and strong classes, this paper made an explicit link between the CM and its implementation. In models that contain *strong interactions* the implementation techniques used to program them deeply influence the results of the simulation. Furthermore they may contradict some foundational agent concepts such as autonomy, resulting in skews in the simulation process. So, refining a CM according to such concepts offers a better understanding of how to implement it. It is necessary to include the analysis of the involved interactions into the conceptual model, if one wants to reduce engineering divergence phenomena.

Therefore, a related methodology would have to check every event that can occur in the environment (moves, agent birth, etc.) to decide which interaction type generated it, and how to implement it appropriately: *strong interactions* requires a specific management of the interaction itself, while *weak interactions* do not.

Another interesting consequence is that both kinds of interaction dynamic may coexist in one single simulation. So it does make sense to implement several interaction dynamics to simulate a particular model. For instance, in [17] a simulation of autonomous robots is proposed. In this model, robots are in charge of recovering objects where some of need to be pushed by several agents. The movements of the agents *(weak interactions)* are managed sequentially while the displacement of a too heavy object requiring that two agents push at the same time *(strong interaction)* is implemented using an *influences/reaction* model: first, forces resulting from the actions of the agents are summed up, and then, the environment "decides" if the objects will finally move.

4.4 Future Works

By using the concepts presented in this paper, our future works suggest a systematic and formal way of implementing both kinds of interaction. To this end, an algebraic model has been proposed [18]. In this model, agents are autonomous entities that act only through explicit *interaction objects.* Interaction objects are structured algebraically as a commutative group. Hence, they are combinable by a + law to represent an aggregation of actions. Negative interaction objects are defined abstractly without any concrete intuitive interpretation, but for the internal definition and computation of the model. So, *strong interactions* are modelled as a sum of elementary interaction objects that define a third interaction object that will be treated correctly by the simulation environment. For instance, the sum of two attempts of reproduction are treated as a single interaction object by the simulator that will actually produce a birth if both of emitting agents want to reproduce themselves. In contrast, *weak interactions* are treated linearly by the simulator and their composition does not produce a new interaction object.

5 Conclusion

This paper has addressed the problem of the *engineering divergence phenomenon* in ABS. This problem is related to the fact that a particular conceptual model may give different outputs according to its implementation. Through two experiments, this paper has shown that the implementation of the agents' interaction is one of the factors which are involved in this phenomenon. The underlying idea of this paper is that this problem can be greatly diminished if the analysis of the conceptual model incorporates some of the key concepts of the implementation. To this end, this work has proposed to identify two different classes of interaction: *weak interactions* and *strong interactions.* The paper claims that this distinction helps to refine the conceptual model by increasing its specification.

Most of engineering divergence phenomena are due to incomplete CM specifications. Hence, conceptual model designers should emphasis the key properties of their system and specify if the interactions among entities are in a strong or a weak mode.

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Using Qualitative Exchange Values to Improve the Modelling of Social Interactions

Maira Ribeiro Rodrigues[1] and Antonio Carlos da Rocha Costa[2]

[1] PPGC – Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil
[2] ESIN - Universidade Catolica de Pelotas, Pelotas, Brazil

Abstract. This paper illustrates the use of a system of qualitative exchange values to support the modelling of social interactions in artificial societies. The system is based on J. Piaget's theory of social exchanges and consists of an algebra of exchange values, a social-reasoning mechanism based on that algebra, and the specification of structures for storing and manipulating such values. We use exchange values both as motivational elements and as regulatory elements that help to guarantee the continuity of the social interactions. We argue that this model can improve the modelling of social agents' interactions and capture more subjective aspects of their social behavior. To elucidate such statement, we use the proposed system to briefly model the political process of lobbying through campaign contributions and draw some conclusions on the dynamics of such scenario.

1 Introduction

Autonomous agents often need to ask help from other agents in order to achieve their goals, and thus, individual goals can also be achieved by such means as coalition formation, task delegation, cooperation or various other kinds of social interactions. In any multi-agent system, the agents may thus be required to be "social", that is, to articulate their own behaviors with the behaviors of other agents, based on their representations of the others agents' behaviors and minds.

In this context, the capacity to reason about the interaction with other agents can be seen as one of the most important requirements for a social agent, in the measure that this reasoning can definitely influence the agent's behavior and decision process.

One approach to the study of such social reasoning, inspired by the social studies on small groups, argues that the decision process about interactions must be influenced mainly by the "social relations" between individuals. In the multi-agent systems area, that approach has lead to the study of evaluations and values assigned to other agents and interactions [10], interconnections between social roles [3] and social organizations [6]. This paper aims to contribute to such approach to social reasoning, by sampling the use of "qualitative exchange values".

The paper builds on the work introduced in [13], which takes Jean Piaget's theory of social exchanges and exchange values found in [11] as a basis for the introduction of a *system of exchange values* to support social interactions in artificial societies.

Piaget's theory defines the exchange values as *performance values,* the kind of values that are assigned to exchanges, accounting for the variations in the energetic and

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motivational elements of that exchanges. These values are not related to utility measures nor to end goals, and are what we consider in this paper.

In contrast, we notice that work on multi-agent systems have made extensive use of a different kind of values, defined by Piaget as *goal values (ends values),* which are assigned to exchanges accounting for their contributions to the goals *(ends)* of the individuals and/or the society. For instance, building on economic theories, there is a whole line of research influenced by game theory [14] and decision theory [2], modelling ends values in a utilitarian, quantitative way. The line of research inspired by the cognitive and social sciences [4] although often opposed to the utilitarian approaches mentioned before, also makes use of end values. This is the case in the work of Miceli and Castelfranchi [10], and Antunes and Coelho [1]. Alternative notions of social structure can be found, e.g., in [8]. In this work, we investigate the application of Piaget's notion of social exchanges in the context of multi-agent systems.

The proposed system of exchange values consists of an *algebra of exchange values,* a *social-reasoning mechanism* based on that algebra, and the *specification of structures* for storing and manipulating such values.

In order to show how our system of exchange values can be applied to real-world situations, we present here a scenario where we model briefly the dynamics of values and of interactions in the *political process of lobbying* through campaign contributions. This scenario was chosen because it is a clear example of the ubiquitous processes involving exchange of values between individuals in a society.

The paper is structured as follows. A brief explanation of Piaget's Theory of Exchange Values is presented in Section 2. The system of exchange values, the specification of the structures to support it, and the social reasoning mechanism based on exchange values, that are fully described in [13], are summarized in Section 3. Section 4 provides the sample application where we try to model, in a simplified way, the dynamics of values in the political process of lobbying. In the latter section, we also present some experiments with the lobbying scenario to show the exchange values dynamics and to draw some conclusions about the systems' modelling capacity. Finally, we present some conclusions in Section 5.

2 Piaget's Theory of Exchange Values

Jean Piaget's Theory studies and formalises the dynamic of values in a way they can form an exchange system. To narrow the focus, so that a formalisation was possible, Piaget centred his attention on the analysis of a special kind of exchange, namely, the exchange of *services* between individuals, i.e., actions that an individual performs *on behalf* of another individual [11].

The values that come out of such exchanges are called *exchange values,* and can be seen as *moral values,* concerning *moral debts* (obligation to perform new services in return to services previously received) and *moral credits* (right to demand the performance of new services in return to services previously given).

One important characteristic of Piaget's notion of exchange values is that exchange values are of a qualitative nature, quantitative values appearing only in the particular case of the modelling of exchanges involving economic values.

Piaget's theory assumes two conditions for the existence of an exchange value system: (i) the individuals involved in an interaction must share a *common scale of values,* to ensure the compatibility of their evaluations of performed and received actions (services); (ii) conservation of the exchange values in time: if there is no conservation of the values in time (i.e., values can suffer depreciation), this fact can risk the continuity of the interactions, and of the functioning of the whole society. Such conservation of values can be achieved by a system of rules (i.e., a *normative structure)* that use rules of two types: *moral rules* and *legal rules.*

If these two conditions hold, a system of exchange value can be seen as a mechanism for regulating (coordinating) the social exchanges of services between agents, guaranteeing their continuity (and thus, the continuity of the functioning of the society).

Complete exchanges between individuals occur in two stages, whose basic forms are as follows: (I) an individual, say α, performs an action on behalf of other individual, say α', acquiring some credit for that action; and, (II) α charges his credit asking α' to perform some action for him, in return. When α' performs that action, the exchange is complete. The first stage consists of four steps:

1. α performs a service on behalf of α' and associates with this action a renouncement value (r_α),representing his *investment* in the action (time, energy, money, emotional expectations, etc.);
2. α' expresses his satisfaction with the received action associating to it a satisfaction value ($s_{\alpha'}$);
3. α' acknowledges the value of the received action by expressing the acknowledgment value ($t_{\alpha'}$);
4. α feels (personally or socially) valued with the acknowledgment of α', and associates to it a reward value (v_α).

At the end of the first stage, the individual α' has acquired a debt ($t_{\alpha'}$) with individual α, and α acquired a credit (v_α) with α'.

Later on, α can charge his credit with α' by requesting that he performs some service in return, a service that benefits α. This gives rise to the second stage of the exchange process:

1. α requests that α' performs an action on behalf of α, based on the credit (v_α) he has in relation to α';
2. α' acknowledges the debit ($t_{\alpha'}$);
3. α' performs a service with a renouncement value (r_α);
4. α acknowledges his satisfaction (s_α) with the service performed by α'.

During the sequence of steps of an exchange stage, the exchange values accumulated by the individuals suffer increments and decrements (positive or negative variations). If the total sum of the variations during a certain stage is null, the system is said to be in *equilibrium* with respect to the exchanges occurring at that stage.

Piaget observes that *nonequilibrium situations* may arise for various reasons, and may occur in any step of the exchange process. For example, when α' — for any reasons — expresses a wrong value ($t_{\alpha'}$) for the satisfaction ($s_{\alpha'}$) he had with the initial service provided by α', or when α' underpays ($r_{\alpha'}$) the debit ($t_{\alpha'}$) he had acknowledged to α (see [11] for a thorough analysis of all possible nonequilibrium situations).

Besides the internal equilibrium within each stage, an equilibrated system must ensure that the acquired values remain the same when the agents pass from stage I to stage II. In other words, the system must provide the means for the *conservation of the exchange values* in time.

That is precisely the role played by the various social means for value conservation called *normative structure.* This structure is a set of rules, of various types (of both moral and legal natures), established in various ways (centralised legal systems, mutual local agreement, private contracts, personal relationships, etc.).

It is important to note that the theory upon which we have developed our work focused on fixed social structures (in the so-called *synchronic approach),* not on evolving social structures (the *diachronic approach),* and our present work lies within that scope limitation [11].

3 A System of Exchange Values for Multi-agent Systems

3.1 Representation, Storage, and Manipulation of Exchange Values

Agents should store four types of values: renouncement (r), satisfaction (s), acknowledgment (t) and reward (v). So, for each interaction in which agent (α) participates, it stores an array of exchange values associated with the other agent involved (α'); that array is called $V_{\alpha\alpha'}$.

Along the various exchange processes, those values can suffer variations and can be decreased or increased. This brings the need for the representation and storage of exchange values, as well as an *algebra* of exchange values, which we sketch below.

In order to have a definite representation for exchange values and their operations, we follow established practices in the area of qualitative reasoning [7]. We take a simplified value set for exchange values, namely the integers {..., –2, –1, 0, 1, 2, ...}, and we define that each increase or decrease of an exchange value during a single step of an exchange process changes such value by an integral number of units, $+n$ or $-n$, according to certain criteria.

Despite the formal quantitative appearance of such representation, it should be clear that it will be used in a qualitative way, due to restrictions on the operations allowed on them: under no circumstance the amount of the *difference* between two exchange values $(x_1 - x_2)$ shall be needed in the reasoning processes, only the information on their relative magnitudes $(x_1 > x_2, x_1 = x_2, x_1 < x_2)$, which makes clear the qualitative *(order-theoretic)* nature of the way in which such values are to be handled.

Considering the two basic stages of an exchange process, with agent α performing a service to agent α', we can define the general ways in which the exchange values are allowed to vary.

We assume that each agent α has an array $V_{\alpha\alpha'} = (r; s; t; v)$ representing the state of the set of its exchange values that are involved in exchanges with agent α'. Then, we define $\Delta_I V_{\alpha\alpha'}$ and $\Delta_{II} V_{\alpha\alpha'}$ to be the arrays representing the ways the exchange values of agent α vary when it interacts with agent α', and $\Delta_I V_{\alpha'\alpha}$ and $\Delta_{II} V_{\alpha'\alpha}$ to be the arrays representing the ways the exchange values of agent α' vary in such interactions.

After the first stage of an exchange process, the value $\Delta_I V_{\alpha\alpha'}(v)$ represents the increase in the credit $V_{\alpha\alpha'}(v)$ that α has on α', awarded to α during that stage. In the same way, $\Delta_I V_{\alpha'\alpha}(t)$ represents the increase in the debt $V_{\alpha'\alpha}(t)$ that α' has with respect to α, assigned to α' during that stage. Then, after each stage of exchange, the arrays $V_{\alpha\alpha'}$ and $V_{\alpha'\alpha}$ should be updated to the corresponding $\Delta V_{\alpha\alpha'}$ and $\Delta V_{\alpha'\alpha}$.

This algebra of exchange values assumes the existence of a common scale of exchange values among the agents involved in the interactions. The definition of this scale depends on the particular application context to which the model is being applied.

3.2 Complementary Information Structures

We assume that agents have access to certain information about other agents and the society, either in the form of an explicit representation found somewhere in the society or in the agents themselves, or in the form of beliefs the agents develop as they operates in the society. To enable agents to reason about the exchange values present in the society, they must have access at least to the following information:

The composition of the society: the agents, their goals and plans, and the actions they are capable of performing (as the *external description* used in [15]).

The exchange-value variation array: the arrays of variations of the exchange values during the current exchange ($\Delta_I V$ and $\Delta_{II} V$).

The state of exchange values: the set of exchange values ($V_{\alpha\alpha'}$ or $V_{\alpha'\alpha}$) accumulated by the agents along the exchanges with other agents. With this information, the agents can identify the mutual credits and debts of the various agents. As this information is cumulative, it must be updated after each exchange process with the information in the variation arrays. We said that the agent has *a positive state of exchange values* when he accumulated more credits (represented by the ‘v’ value) than debts (represented by the ‘t’ value), and the contrary for a *negative state of exchange values.* A *null state of exchange values* is characterized when the agent’s accumulated credits and debts are the same.

The history of exchange values: each entry should contain the time that an exchange took place, the action performed or received by agent α, the identification of agent α' involved in the exchange, and the variation array associated with the exchange. This information enables a long term analysis of the dynamics of exchange values during the simulation.

The set of norms and agreements: this is established during the exchange process in order to have an agreement on the operations that guarantee the conservation of the exchange values in time.

The exchange-value strategies: the set of rules and criteria used by the agent to choose the interaction partners and to elaborate interaction proposals that result in a desirable next state of exchange values. The various agents in the society may behave in different ways according to their exchange-value strategies.

3.3 A Social-Reasoning Mechanism Based on Exchange Values

We now show how the system of exchange values defined in the previous section can support a social-reasoning mechanism for exchange values. The social-reasoning mechanism we describe here is directed towards supporting what seems to be the two main goals of introducing exchange values in multi-agent systems, namely: the continuity and regulation of social exchanges, and the use of exchange values to orient the agents' planning and decision making with respect to exchange processes.

The social-reasoning mechanism operates in three phases: *before the exchange, during the exchange* and *after the exchange.* The state diagram of the whole value-based social reasoning mechanism is shown in Figure 1.

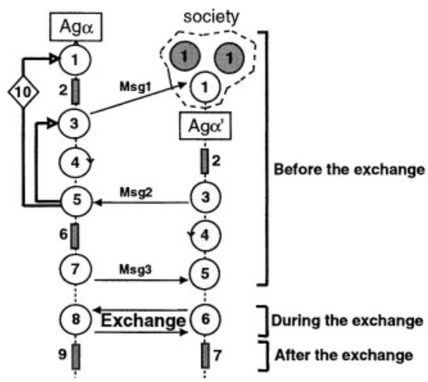

Fig. 1. State Diagram of the Social-Reasoning Mechanism Based on Exchange Values.

Reasoning Before the Exchange

An agent in a multi-agent system can initiate an exchange, and so activate its value-based social reasoning mechanism, according to the following reasons: (i) the agent is not capable of performing an action needed for executing a plan that achieves a goal to which it has committed, so it requires that another agent performs that action as a service; (ii) the agent is capable of performing the actions needed to execute the plans for its goals, but prefers that another agent performed it as a service; (iii) the agent does not need any action at the moment — its current plans are independent of the other agents — but intends to earn credits on other agents by offering them some service. The reasoning mechanism in this phase is an extension of the cognitive model of social reasoning proposed by [5], with the addition of a computation on exchange values. We have also extended this combined mechanism to form an unified social reasoning mechanism that can be integrated with existing interaction models in multi-agent systems literature (e.g., the Contract Net [16] and the Dependence-based Coalitions [15,5]).

Given the agent's motivation and state of exchange values, the social reasoning before the exchange consists of a computation to choose, with the assistance of the agent's strategy: (i) the agents and types of exchange proposals that suit better the target exchange, and (ii) which agents are more likely to accept the proposal. The chosen proposal is the one that results in a desirable next state of exchange values according to the agent's value-based strategy. We define four basic types of exchange proposals, as follows.

Type 1 – Requesting a service in exchange of another service. Here the agents follow the first and second stages of the exchange process.

Type 2 – Requesting a service in exchange of a credit. Here the agents follow the first stage of the exchange process. After the exchange process the agent that requested the service acquires a debt and the agent that performed the requested service acquires a credit that can be charged later on.

Type 3 – Requesting a service in exchange of a previously acquired credit (charging). Here the agents follow the second stage of the exchange process. In this case the proponent will be charging a credit acquired in a previous exchange, and it expects to get in return the requested service.

Type 4 – Offering a service in exchange of a credit. Here the agents follow the first stage of the exchange process. The agent that offers the service acquires a credit and the agent that accepts the offer (e.g., receives the offered service) acquires a debt.

The sequence of reasoning steps in the proponent's (α) and the recipient's (α') social reasoning before the exchange, as seen in Figure 1, is as follows.

The Proponent's social reasoning. The social reasoning starts with the identification of the motivation for the exchange (state 1) and then passes to the first computation of exchange values (state 2). During this state the proponent's reasoning consists of: (i) choosing, based on the criteria defined in the agent's strategy, the possible partners for the interaction; (ii) choosing the associated types of proposals and sort the set of possible partners; (iii) elaborating the exchange proposal for each selected partner with the specification of the norms that will guarantee the conservation of the values (e.g. credits and debt) acquired as a result of the exchange. Examples of possible associations are: associate proposal type 3 to agents with which the proponent has credits; associate proposal type 2 to agents on which the proponent depends for a certain service and with which it does not have credits; and so forth. After the first computation of exchange values (state 3), the proponent can either send a proposal only to the first agent in the set of possible partner, or send it to all the agents in that set (Msg1). Then, it waits for the reply message (state 4). When the reply message arrives (Msg2), the agent passes to next step to analyse the situation (state 5). It can return to state 3, in case of a negative answer or passes to state 6, in case of a positive answer. Also, if a request charging a credit (proposal of type 3) receives a negative answer, the proponent can request the compensations or enforce the punishments as established in the norms associated with the proposal that originated the credit. In the second computation of exchange values (state 6), the proponent must choose between the agents that have answered the proposal affirmatively and check whether they have agreed with the proposed norms or changed them. If the norms were accepted, the proponent sends an acknowledgment to the selected partner (Msg3) and the exchange process begins (state 8).

The Recipient's social reasoning. The sequence of the recipient's (α') social reasoning is as follows. When the agent receives a message (Msg1), it activates the value-based social reasoning mechanism and begins the computation of exchange values (state 2). It consists of selecting the acceptable proposals and sorting them according to the criteria defined in the recipient's strategy. In case the agent receives a proposal of type 4 (offering a service), it must analyse if the offered service is in fact useful at the time. In case it is not, the agent can counter-propose another service in the reply message. Also, in this step the agent must analyse the regulations (i.e., norms) proposed by the proponent. If the agent does not agree with them, it can counter-propose the adoption of different norms in the reply message. After this analysis, the reply message is elaborated (Msg2). The recipient agent should send a positive reply message to the agent in the set of potential partners which seems to lead to the best state of exchange values, and a negative answer for the agents which were dismissed in the previous step. Then it waits for the acknowledgment message. When the acknowledgment (Msg3) arrives, the agent passes to the next step to analyse the situation. In case of a negative answer, the reasoning process returns to state 3 or, in case of a negative answer, the exchange process begins and the social-reasoning mechanism passes to the next phase (reasoning during the exchange).

Reasoning during the Exchange

In this phase the exchange of actions take place. The sequence of events depends on the type of proposal agreed upon by the agents and follows the order established in stages I or II of the exchange process. During the exchange, the social reasoning of the agents involved consists of computing the variation of the exchange values, represented by the arrays $\Delta_I V_{\alpha\alpha'}$ and $\Delta_{II} V_{\alpha\alpha'}$ for agent α, and $\Delta_I V_{\alpha'\alpha}$ and $\Delta_{II} V_{\alpha'\alpha}$ for agent α'. The variations in the exchange values can be positive or negative, depending on the type of exchange value and on which agent performed or received the action.

Reasoning after the Exchange

After the exchanges have been performed and the variations in the exchange values have been computed, the social-reasoning mechanism proceeds by updating the agents' exchange-value structures — the history of exchange values and the state of exchange values. Also, the agents must store in their data structures the set of norms or agreements upon which they have agreed before the exchange, so that they are aware of their duties and rights in future exchanges.

4 Modelling the Political Lobbying Process

In this section we use our system of exchange values to model, in a simplified way, the political process of lobbying through campaign contributions. With this scenario we intend to observe the capacity of the proposed system to model more subjective aspects of interactions, as observed in human societies, and, at the same time, to provide regulatory elements for guaranteeing the continuity of social interactions. We have chosen the lobbing process because it is a clear example of the ubiquitous processes involving exchange of values between individuals in a society. The exchanged services (or actions) in this scenario can refer to things (e.g., monetary contributions, presents, votes) or subjective ones (e.g., promises, faithfulness, gratitude gestures).

In modelling that scenario, we identify three types of agents: *politicians, lobbyists,* and *voters.* The social context in which they are embedded is a political election, and each of them has its own goals and interests in relation to resource destination alternatives. The scenario is characterized by two different situations: before the election (the campaign situation) and after the election (the governmental action situation). The agents' goals and strategies for the two situations may vary, leading to different behaviors and desired states of exchange values. Only a brief analysis of the scenario is given here (see [12] for a more comprehensive analysis based on [9], although the latter uses a different approach to study the lobbying process).

4.1 The Normative Structure

For simplicity, in this scenario we consider a *normative structure* (set of legal rules and moral norms) with only two `moral` norms to guarantee the conservation of the exchange values. The norms must define an obligation and a punishment for the non complying agent. The norm referred to by `norm1` asserts that every agent that receives a proposal charging a credit (type 3) has the deadline of a certain number of time units to perform the required service in return and the punishment for not complying with the norm is the depreciation of the reward value that the non-compliant agent will suffer in future interactions. The norm referred to by `norm2` asserts that every agent that acquires a debt has the obligation to take the initiative to pay the debt by offering a service to the agent that has the correspondent credit; the punishment for not complying is also the depreciation of the reward value. This depreciation is reflected on the non-compliant agent's state of exchange values and history of exchange values. If we consider that the agent's state of exchange values represents its "social image", this punishment can also be seen as a "moral" depreciation of the non-compliant agent in front of the other agents in society. Other types of punishment can also be used in addition to the moral punishment. For example, if in the system the agents are endowed with particular resources, the punishment for the non compliant agents can be to lose some resource possession.

4.2 Description of the Agents

The Politician Agent

Goal: when in campaign, its goal is to win the political election. When in government, it makes choices on resource destination, considering what it believes to be more appropriate to the development of the community as a whole. At the same time, the politician has to consider whether the choices are in agreement with the interests of particular groups (represented by the lobbyist agents) and of the general population (the voters), with the intention of receiving in exchange votes and financial contributions to the next political campaign.

Desired state of values: Usually, negative or null before the election and positive after the election. A negative or null state of values indicates that the politician received some services from other agents (lobbyists or voters) either by requiring these services in exchange of some credit, or by charging them in exchange of previously acquired credits. This may be a good situation before the election, given that these services are probably financial contributions to the campaign or voting intentions. A positive state of values after the election indicates that not only has the politician agent paid its debts (acquired before the election) with lobbyist and voter agents, but it has also gained some extra credits with these agents by performing services on their behalf.

Strategies to achieve the desired state of values: We identify two types of strategies: one based on credits, and the other based on debts. They try to capture two real situations, the first where a politician supports his campaign on his past achievements when he has gained prestige and recognition with voters and lobbyists (first strategy), or the second situation where the politician supports his campaign on promises of great achievements (second strategy). To use the first strategy the agent must have an initial positive state of exchange values (i.e., credits with lobbyists and voters) and should prefer to send exchange proposals of type 3. The second strategy must be used when the agent has a negative or null state of exchange values (i.e., no credits with lobbyists and voters). It indicates that the agent must send exchange proposals of type 2.

The Lobbyist Agent. It represents the interests of a particular group of people (e.g., big companies or another political party). When the politician is in government, the lobbyist's goal is to influence the politician to choose a particular destination of resources by either offering him financial contributions to be used in the political campaign or by charging such decisions on contributions given to the previous election. The lobbyist agent's *desired state of values* is positive before the election (i.e., credits with politician agents) and negative or null after the election (i.e. he charged the acquired credits in exchange of a desired course of action). The *strategy* it uses to achieve the desired state of values is to offer financial contributions to (and request political favours from) politician agents.

The Voter Agent. When the politician is in campaign, its goal is to choose the politician whose proposals on resource destination are best suited for its interests and the interests of its community. The voter agent's *desired state of values* is positive before the election (i.e., credit with the politician agent) and negative after the election (i.e., it has charged its credit with the politician agent in exchange of some desired course of action). The *strategy* used to achieve the desired state of values is to accept required services from — and offer the voting intention to — the politician agent.

Several aspects of those agents' behaviour can be captured by the analysis of the information on exchange values. Some of them may be incorporated into the agents' strategies to help them choosing the preferred partner for the exchange. Examples are:

1. the fidelity of the voter with respect to the politician (by analysing the former agent's exchange values history);
2. the politician commitment with lobbyist agents (by analysing the politician agent's history and state of exchange values);
3. the politician with most voting intentions (by analysing the politician agent's state of exchange values);
4. the services that are most required by voters and lobbyists (by analysing the politician agent's history of exchange values).

4.3 Description of the Scenario

To represent the agents' interests regarding the possible resource destination alternatives $\{a1, a2, .., an\}$, we use one of the elements in the set $\{-1, 0, +1\}$, where -1 indicates that the agent does not support the destination of resources to the alternative, 0 indicates that the agent has a neutral position with respect to the alternative, and +1 indicates that the agent supports the destination of resources to the alternative. Additionally, the lobbyist agent must associate with the alternative of interest the amount of financial contribution he is willing to give in exchange of it.

The composition of the society is represented with a structure similar to the external description that contains, besides the information about goals, plans and possible actions, the agents' interests regarding the resource destination alternatives.

To describe the proposed scenario, we define a society with five voter agents (E_1,..,E_5), two politician agents (P_1 and P_2) and two lobbyist agents (L_1 and L_2). The external description for the composition of the society is shown in table 1.

In this sample application of the proposed system we will present three experimentations, each one presenting different contexts and strategies for the agents, so we can observe the influences of these elements upon the agents' behaviour regarding the interactions.

For each experimentation we will draw some conclusions about the use of qualitative exchange values to model social interactions.

Table 1. Composition of society in the political lobbying scenario.

Ag	*Goals*	*Actions*	*Plans*	*Interests*			
				a1	a2	a3	a4
P1	Win the election (WE)	a1,a2,a3,a4	WE:= FC;V.	+1	+1	−1	0
P2	Win the election (WE)	a1,a2,a3,a4	WE:= FC;V.	0	+1	+1	−1
L1	Represent particular interests (RPI)	Financial Contribution (FC)	RPI:= a1;a3.	+200.00	−1	+300.00	0
L2	Represent particular interests (RPI)	FC	RPI:= a2;a3.	−1	+300.00	+200.00	0
E1	Represent the community interests (RCI)	Vote Intention (V)	RCI:= a1;a4.	+1	0	−1	+1
E2	RCI	V	RCI:= a1;a2.	+1	+1	−1	0
E3	RCI	V	RCI:= a1;a3.	+1	0	+1	−1
E4	RCI	V	RCI:= a1;a4.	+1	0	−1	+1
E5	RCI	V	RCI:= a2;a4.	0	+1	−1	+1

4.4 Experimentation I – Before the Election

For this experimentation we will show a simple example of the activation of the proposed social reasoning mechanism in a prototypical phase of an interaction. According to the politician agents' strategies, if they have no credits with the lobbyist agents, they should send an exchange proposal to the one offering the higher monetary contribution for the adoption of some compatible (non conflicting) alternative to resource destination in exchange of a future political favour. A possible part of the politician agent P_1's social reasoning is as follows:

1. Interaction motivation: need of financial contribution;
2. First computation of exchange values: (i) Possible partners selection: L_1, L_2; (ii) Type of proposal and sorting: L_2 with proposal type 2, L_1 with proposal type 2 (criteria: higher monetary contribution); (iii) Elaborate exchange proposal: `proposal(type_2,contribution=300.00,norm_1)`.
3. Sending the exchange proposal to L_2;
4. Waiting for the answer;
5. Receiving the answer message from L_2;
6. Analysing the situation: pass to next state;
7. Second computation of exchange values: (i) Norms: OK.
8. Sending the acknowledgment;
9. Performing the exchange process. The sequence of events follow the Stage I of the exchange process, with agent P_1 receiving the service `(contribution=300.00)` from agent L_2. Computation of the array of exchange-value variation: $\Delta V_{L_2 P_1} = \{r = -1; s = 0; t = 0; v = +1\}$ and $\Delta V_{P_1 L_2} = \{r = 0; s = +1; t = -1; v = 0\}$.

After the exchange, the agents' update their exchange-value structures. Agent P_1 must add a positive variation to its satisfaction value (s), and a negative variation to its acknowledgment value (t) in the table entry associated with agent L_2. On the other hand, the agent L_2 must add a negative variation to its renouncement value (r), and a positive variation to its reward value (v) in the table entry associated with agent P_1.

As a result of the exchange, agent P_1 has acquired a new debt ($\Delta V_{P_1 L_2}(t)$) with L_2, and L_2 acquired a new credit ($\Delta V_{L_2 P_1}(v)$) with agent P_1.

If P_1 is elected, L_2 can charge the previously acquired credit asking P_1 to perform some service in its behalf, such as destining governmental resources in a way that favours the lobbyist personal interests. The lobbying was successful.

The same situation may occur with a voter agent that has a credit with the elected politician and wants to charge it in exchange of, for example, governmental investments in the local community.

4.5 Experimentation II – After the Election

Assuming that the politician agent P_1 was elected, once he had more compatible interests with voter agents, and he is concerned in providing the voters requests, he must pursue a positive state of exchange values (the politician agent's current state of values is negative since it acquired many debts before the election). This behaviour can be represented with a strategy asserting that the agent should send exchange proposals offering services (type 4) and accept exchange proposals charging credits (type 3), so in both cases, the politician agent will be paying his debts with the agents who elected him.

Let us suppose that the politician agent P_1 received exchange proposals from agents E_2, E_5, L_2 and E_1, asking for some resource destination in exchange of credits acquired before the election (proposal type 3). A possible part of the politician agent P_1's social reasoning is as follows:

1. Receiving a proposal:
   L_2 `proposal(type_3,a2,norm_1);`
   E_2 `proposal(type_3,a2,norm_1);`

E_5 `proposal(type_3,a2,norm_1);`
E_1 `proposal(type_3,a1,norm_1).`

2. Computation of exchange values: (i) Selection: L_2,E_2,E_5,E_1 (proposal type 3); (ii) Norms: OK; (iii)Sorting of potential partners: E_2,E_5,L_2,E_1 (criteria: voter agents and requests for alternative $a2$).
3. Sending the answer message to E_2,E_5 and L_2;
4. Waiting for the acknowledgment;
5. Receiving the acknowledgment message;
6. Performing the exchange process. Agent P_1 performs the service (`resource destination to` $a2$) that benefits agents L_2,E_2 and E_5. Computation of the array of exchange-value variation: $\Delta V_{L_2 P_1} = \Delta V_{E_2 P_1} = \Delta V_{E_5 P_1} = \{r = 0; s = +1; t = 0; v = -1\}$ and $\Delta V_{P_1 L_2} = \Delta V_{P_1 E_2} = \Delta V_{P_1 E_5} = \{r = -1; s = 0; t = +1; v = 0\}$.

The politician agent P_1' chose to accept the requests from agents E_2,E_5 and L_2 asking for alternative $a2$, since it will satisfy a greater number of agents. Then, the social exchange take place with agents L2, E2 and E5. In this case, both the lobbying and the community interests were successful.

As a result of the exchange process, the politician agent paid his debts with other agents and, consequently, achieved a null state of exchange values (see table 2). It also indicates that the politician agent is keeping his moral commitments with other agents and tending to a positive state of exchange values – the politician agent's desired state of exchange values, as described in section 4.2.

Table 2. Politician agent's state of exchange values before (a) and after (b) the exchange process.

(a)

Agent	v	t	s	r
L2	0	−1	+1	0
E2	0	−1	+1	0
E1	0	−1	+1	0
E5	0	−1	+1	0

(b)

Agent	v	t	s	r
L2	0	0	+1	−1
E2	0	0	+1	−1
E1	0	−1	+1	0
E5	0	0	+1	−1

With a more subjective analysis we can say that, considering the state of exchange values as reflecting the agents' social image in front of others, by keeping his moral commitments with other agents the politician agent is also pursuing a positive social (and political) image. This aspect of behaviour regarding the interactions is clearly observed in human societies and could be captured by the use of exchange values in the agents' social reasoning mechanism.

4.6 Experimentation III – After the Election

Now, let us suppose that, after the election, the politician agent P_1 adopts a different behaviour regarding the interactions: he is not concerned in providing the voter agents' requests but in supplying particular interests. This behaviour can be represented with a strategy asserting that the agent should give priority to exchange proposals from lobbyist agents and do not offer any services to other agents. Also, the new adopted strategy asserts that he must not concern in accepting proposals with conflicting interests.

Again, we suppose that the politician agent P_1 received exchange proposals from agents E2, E5, L2 and El, asking for some resource destination in exchange of credits acquired before the election (proposal type 3). A possible part of the politician agent P_1's social reasoning is as follows:

1. Receiving a proposal:
   L_2 `proposal(type_3,a3,norm_1);`
   E_2 `proposal(type_3,a2,norm_1);`
   E_5 `proposal(type_3,a2,norm_1);`
   E_1 `proposal(type_3,a1,norm_1).`
2. Computation of exchange values: (i) Selection: L_2,E_2,E_5,E_1 (proposal type 3); (ii) Norms: OK; (iii)Sorting of potential partners: L_2,E_2,E_5,E_1 (criteria: lobbyist agents).
3. Sending the answer message to L_2;
4. Waiting for the acknowledgment;
5. Receiving the acknowledgment message;
6. Performing the exchange process. Agent P_1 performs the service (`resource destination to` $a3$) that benefits agent L_2. Computation of the array of exchange-value variation: $\Delta V_{L_2 P_1} = \{r = 0; s = +1; t = 0; v = -1\}$ and $\Delta V_{P_1 L_2} = \{r = -1; s = 0; t = +1; v = 0\}$.

According to the new strategy described above, the politician agent P_1's social reasoning chose to accept the request from the lobbyist agent L_2, even with the observation that the requested alternative on resource destination $(a3)$ is conflicting with his interests and the interests of the community (represented by the voter agents). In this case, the lobby was successful.

As a consequence of the exchange process we must notice that, although it resulted in a valuation of P_1 by L_2, once he paid his debit with L_2 ($\Delta V_{P_1 L_2}(t) = +1$) by performing the resource destination to action $a3$ in exchange, it also led to a depreciation of P_1's state of exchange values by the voter agents, since the performed action was conflicting with their interests. So, we observe that in this situation, in contrast with the former one, the politician agent's state of values became negative (see table 3) – the opposite of the politician agent's desired state of exchange values described in section 4.2.

Table 3. Politician agent's state of exchange values before (a) and after (b) the exchange process.

(a)

Agent	v	t	s	r
L2	0	−1	+1	0
E2	0	−1	+1	0
E1	0	−1	+1	0
E5	0	−1	+1	0

(b)

Agent	v	t	s	r
L2	0	0	+1	−1
E2	−1	−1	+1	0
E1	−1	−1	+1	0
E5	−1	−1	+1	0

Considering that the voter agents' strategies take into account the politician agents' state of values, and thus it has influence upon the formers' behaviour regarding the interaction partner selection, we can say that probably the politician agent P_1 will not have a good performance in future elections.

One sees that by monitoring the evolution of the exchange values of a successively re-elected politician, along a series of elections and corresponding periods of government activity, a picture of his tendency to keep commitments with either electors or lobbyists can be produced, and the net debts and credits he developed can be adequately estimated.

With this experimentation, we also observe the role of exchange values in the formation of the agents' social image, which can be positive or negative depending on the choices made by the agents regarding the interactions and the actions performed in society.

5 Conclusions

We have presented a system of exchange values, based on Jean Piaget's notion of qualitative exchange values, to support social interactions in artificial societies. In the proposed system, we use exchange values both as *motivational elements* in the interactions between agents, and as *regulatory elements* with respect to the *equilibrium* and the *continuity* of their exchanges. We have argued that such characteristics can lead to an improvement in the modelling of social agents' interactions, since they capture some of the moral aspects of such interactions.

With the sample application presented in the present paper we could draw some conclusions on the use of the system of exchange values to model social interactions. First, that the use of exchange values can capture some aspects of social behaviour, like observed in humans societies. We observe, for example, that the proposed system was capable of modelling the fact that social interactions are influenced by the values individuals assign to each other and to the interactions.

Also, the scenario shows that along with the interactions the exchange values are seen by the agents as social commitments and are capable to express their social image (i.e., the way they are seen by the other agents regarding the interactions and the actions they perform in society). As such, the continuity of interactions is motivated, in a certain way, by the agents' desire (concern) of keeping this social image. So, the proposed system of values may also contributes towards the design of a practical *social regulation systems* that could help in keeping a reasoned continuity of the social exchanges.

Investigate the relation between J. Piaget's Theory and Homans Theory of Social Exchanges, including the role and definition of normative structures in both theories, is something that we plan to do.

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Bilateral Tradings with and without Strategic Thinking

Shinji Tomita and Akira Namatame

Dept. of Computer Science,
National Defense Academy, Yokosuka, 239-8686, JAPAN,
{g41044,nama}@nda.ac.jp

Abstract In classical economics theory, the market clearing price is determined by the aggregate demand and supply functions of the market. However, in the real world, there are many situation where individuals having imperfect knowledge will trade bilaterally rather than trading at a global market price. Epstein and Axtell proposed a model of bilateral trading in a mobile environment. Individuals may be willing to settle for a price less profiting to themselves. This paper seeks to make clear the characteristics of bilateral trading under the poor society and the rich society. We compare the bilateral trading models with global price, with local price, and with strategic interaction. We especially investigate collective market behavior with and without strategic interaction at individual levels. We show that the model with local market price without strategic interaction shows results close to that found in a global price model. These two models create stable and equitable market behavior, however, they are inefficient. We show that agents with strategic consideration exhibit unstable but the most efficient market behaviors.

1 Introduction

Classical economics theory assumes that the price and quantity exchanged of a particular good in a market is determined by the demand and supply of that good. The demand and supply of a good in a market is determined by the individual demand and supply of all individuals found in that market. Here, individual demand is defined as the quantity of a good an individual is willing to buy at each price, while supply is the quantity of a good an individual is willing to provide for sale at each price. The market demand and supply are then defined as the sum aggregate of individuals' demands and supplies [13].

However, in the real world, there are many situations where individuals having imperfect knowledge of market will trade bilaterally rather than trading at a global market price [1][2][4]. Epstein and Axtell proposed a model of bilateral trading in a mobile environment [7]. Their model seeks to make clear the characteristics of bilateral trading in mobile environments. Their model, which is also known as the Sugarscape model, consists with $N x N$ number of cells as shown in Fig. 1. Agents are free to move around in the environment, agents moving off the top edge of the environment will wrap around to the bottom edge, and vice versa. The same is true for

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agents moving off the left or right edge of the environment. Each cell has a fixed amount of foods. In the Sugarscape model, there are two foods A and B available in the market. These foods are found in the environment in two “mountains” of Food A and two “mountains” of Food B. As they move away from the peak of these “mountains”, smaller amounts of foods are found. Fixed amounts of both Food A and Food B are found at each spot in the environment.

Individuals do not usually know what the market demand and supply are. Therefore, they do not know the market price. Individuals rarely know anything other than their own demand and supply. Thus, for classical economics theory to hold, there is a need for a “magic auctioneer” who announces the market price at which each individual will then trade. This is an unrealistic assumption. While such a “magic auctioneer” may exist in stock markets and futures trading, most markets in the real world do not have a “magic auctioneer” who announces the market price. Individuals thus lack the knowledge needed for classical economics theory of price determination to hold. In such a case, if the classical economics theory of profit maximisation is true, individuals will seek to carry out bilateral trade at a price and quantity most profitable to themselves. Thus, rather than trading at a global market price, individuals will trade bilaterally. Such a course of action may also include the use of strategic interaction on the part of individuals. Depending on the elasticity of their demand and supply, individuals may be willing to settle for a price less profiting to themselves. When the price of the bilateral trading is determined by individuals, it may not benefit both individuals equally. When strategic interaction comes into play, one individual may benefit more than the other during bilateral trading.

We show the following results with simulation: For the global market, the price is obtained from the demand, as determined by each individual’s utility function. However, as individuals are free to move in the environment without strategic interaction does not take place, this demand is communicated over time throughout the whole environment. It is similar to price determination in a global market with a time lapse. When strategic interaction is introduced at individual levels in bilateral trading, the price at which trading takes place is highly affected. Now, as individuals use the power that comes with possession of excessive amounts of a certain food, they are able to affect the trading price so as to benefit themselves. This is the model most close to a real world model, as monopolies set prices higher to reap more profits, and individuals will buy goods at different prices according to the urgency of their needs.

2 The Models

In the Sugarscape model by Epstein and Axtell, there are two goods available in the market. For simplicity, we will assume that the two goods are two types of food, Food A and Food B. Individuals require both types of food for survival, though in different quantities, as given by their metabolism. When individuals accumulate a certain amount of food, they will introduce a new individual into the environment. Individuals are free to move in the environment and harvest the food found, and they are also free to trade foods with their von Neumann neighbours. In this case, they will move to a location in the environment that will maximize their welfare. This is affected by the amount of both Food A and Food B found in the location, as well as the possibility of trade with adjacent individuals. The distance an individual is able to see and move is different for each individual.

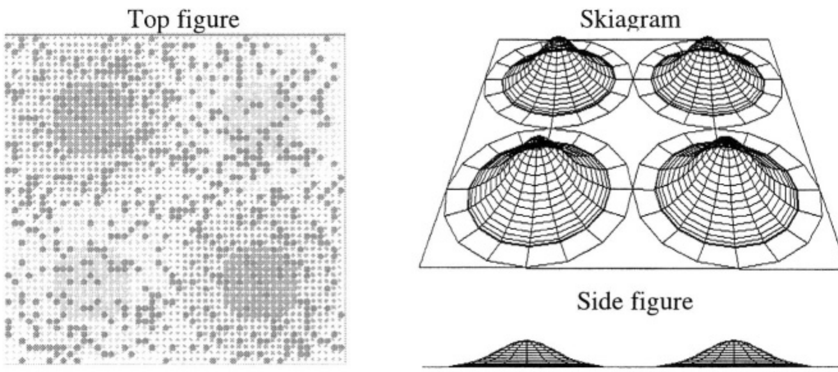

Fig. 1. The Sugarscape model

Individuals consume Food A and B at a rate of m_A and m_B, their individual metabolism for Food A and Food B respectively, per cycle. At any given time, each individual has an amount s_A of Food A and s_B of Food B. The number of cycles before an individual starves from lack of a particular food is given by t_A and t_B, where $t_A = s_A/m_A$ and $t_B = s_B/m_B$ respectively. Individuals are welfare maximizing, and their utility is given by the Cobb-Douglas function given by [2],

$$W = {s_A}^{a} \, {s_B}^{1-a} \tag{2.1}$$

where $a = m_A/(m_A + m_B)$

We assume that individuals are profit maximizing. Individual profits are manifestation of welfare and thus we can assume that individuals are welfare maximising. Individuals will seek to trade and accumulate both types of foods so as to maximize the value of this utility function. As individuals are free to move around the environment, they will seek out areas whereby they can accumulate food so as to maximize their welfare. Also, since trading with neighboring individuals can also be a source of food, they will also seek out areas where other individuals are found.

The marginal rate of substitution between Food A and Food B is given by

$$MRS = t_B/t_A \tag{2.2}$$

Thus, individuals will seek to obtain Food A if their *MRS* is bigger than 1, and Food B if their *MRS* is smaller than 1. For both partners engaging in bilateral trading to benefit, they must trade at a price in between the values of their *MRS*. The price *p* is the quantity q_B of Food B an individual is willing to trade for the quantity q_A of Food A. Therefore,

$$p = q_B / q_A \tag{2.3}$$

Below, we consider three models for determining the market clearing price *p*, namely (1) The Sugarscape model with global price, (2) The Sugarscape model with local price, (3) The bilateral trading with strategic interaction.

Model 1: Sugarscape model with global price determination. The global price model can also be called the classical economics model. In this model, the market price at which bilateral trading take place is global across the market, and is derived from the demand of all individuals, given by their *MRS,* in the market. In other words, the global market price is the average of all individual *MRS* given by

$$p = \sum_{i=1}^{n} MRS_i \Big/ n \tag{2.4}$$

where n is the number of individuals in the market.

Model 2: Sugarscape model with local price determination. In this model, the price at which bilateral trading take place depends on the individuals taking part in the trading. Individuals will decide on a price range at which they are willing to trade at, given by their individual *MRS* and welfare functions, and they will trade at a price equally benefiting to both parties involved in the trading. Therefore the local market price of Individual i with MRS_i and Individual j with MRS_j is determined by the geometric mean of these two *MRS* given by

$$p = \sqrt{MRS_i \times MRS_j} \tag{2.5}$$

Model 3: Bilateral trading with strategic interaction. This model incorporates strategic interaction base on the elasticity of the individual's demand. Individuals who have a stronger need for a good will tend to be willing to pay more for that good, and those with a lesser need will tend to be less willing to pay [3][18]. Thus, depending on the needs of the individuals, we can have cases where both individuals insist on trading at their own prices, or one individual willing to trade at the price proposed by the other individual, or where both individuals are willing to trade at each other's price. In the first case, trade will not take place, since a price cannot be agreed on, while in the second case, trade will take place at the price set by one of the individuals, and in the third case, the price will be the same as for the local price model without strategic interaction, i.e. the price is the geometric mean of the *MRS* of the two individuals involved. This is similar to the hawk-dove game, where the hawk is the individual who insists on his own price and the dove is the individual who yields to the other's price [17].

In this model, agents first determine which food they are in need. Agents demand Food A or Food B based on their *MRS,* as determined by the rules below.

$$MRS > 1 \rightarrow \text{Demand Food A}$$

$$MRS \leq 1 \rightarrow \text{Demand Food B} \tag{2.6}$$

They will then determine the urgency of their needs. This is done through a threshold value k. Agents are not in urgent need of a food if their *MRS* falls between the threshold and the inverse of the threshold, and they will demand their own *MRS* as the price for trade. Otherwise, agents are in urgent need of a food and will be willing to forgo their own *MRS* as the price for trade.

$$\tfrac{1}{k} \le MRS \le k \rightarrow \text{demand own } MRS$$

$$(MRS < \tfrac{1}{k}) \text{ or } (MRS > k) \rightarrow \text{forgo own } MRS \tag{2.7}$$

For our experiment, we will look at the characteristics of trading in the local price model with strategic interaction when the value of the threshold k is set at 2.

After these are determined, agents will seek out other agents who do not demand the same food, i.e. if an agent demands Food A, that agent will seek out another agent that demands Food B. When such an agent is found, the agents will attempt to trade. Depending on the urgency of their needs, agents will seek to either trade at their own price, given by their *MRS,* or at the price of the other agent involved in the trade. If both agents attempt to trade only at their own prices, trade does not take place. If both agents are willing to trade at the price of the other agent, the geometric mean of their *MRS* is used as the price, similar to the local price model without strategic interaction. If one agent seeks to trade at his own price and the other agent is willing to forgo trading at his own price, the price at which trading takes place will be the *MRS* of the former agent. This is similar to the hawk-dove game with the following strategies:

S_1 : Demand own *MRS* (Hawk)

S_2 : Forgo own *MRS* (Dove)

The price at which trade will take place is determined by the rules in Table1. Trading takes place if both agents are able to benefit from trading, i.e. both agents will enjoy a higher value for their utility by trading.

Table 1. Rule of price determination

Agent *i* \ Agent *j*	S_1(Hawk)	S_2(Dove)
S_1(Hawk)	Trade does not take place	MRS_i
S_2(Dove)	MRS_j	$p = \sqrt{MRS_i \times MRS_j}$

3 Experimental Results

For the purpose of our experiments, we use an environment of 50 by 50 cells, and start with a population density of 10%. Individuals will be required to accumulate 25 units of both Food A and Food B before being able to introduce a new individual into the environment. Individuals will be able to see from 1 to 6 locations away. Their metabolisms for Food A and Food B, m_A and m_B, are in the range of 1 to 4, and each individual will start with 4 to 8 units of Food A and B each. We set up two types of society to analyze the character of each rule in the different environment. It is the society that one is poor society and another is rich society. In the poor society, each location will have between 1 to 4 units of Food A and Food B each. In the rich society, each location will have between 1 to 8 units of Food A and Food B each. This is spread out in 4 "mountains", with 2 for Food A and 2 for Food B.

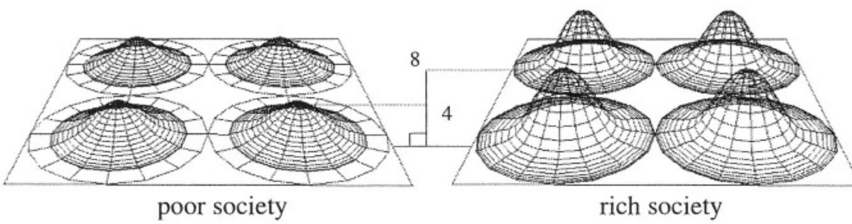

Fig. 2. Two types of society

3.1 Price Stability

We shall start by comparing the characteristics of the average price in the three trade models. We will compare the models in terms of the average trading price p_t per cycle. We compare the average trading prices between cycles, p_t and p_{t+1}.

Plotting the value of the average of prices in each cycle against the value of the average of prices in the previous cycle, we obtain Fig. 3(a1) ~ (b3). The x-axis represents the price p_t and y-axis represents the price p_{t+1}. Left side Fig. (a1), (a2) and (a3) shows fluctuations in the price under the poor society. Right side Fig. (b1), (b2) and (b3) shows fluctuations in the price under the rich society.

Table 2 shows the maximum value of the change with each mode under the poor society and the rich society.

In the poor society, we shall see that the Sugarscape model with global price results in the most stable price, whereas that of the bilateral trading with strategic consideration results in prices with great fluctuations. From Fig. 3(a1), we can see that there is little fluctuation in the global price between cycles. The maximum value of the change in the global price is 1.2 and averages around the value of 1 because agents have their metabolic rates uniformly and randomly distributed. At any point in time, there are just as many agents demanding Food A as there are agents demanding Food B. This gives us an average marginal rate of substitution *(MRS)* of 1. The change in prices also shows the effect of the invisible hand. As prices increase, agents in demand for Food A will trade more amounts of Food B for Food A. Agents with an abundance of Food A will thus gain in Food B. As the demands of those

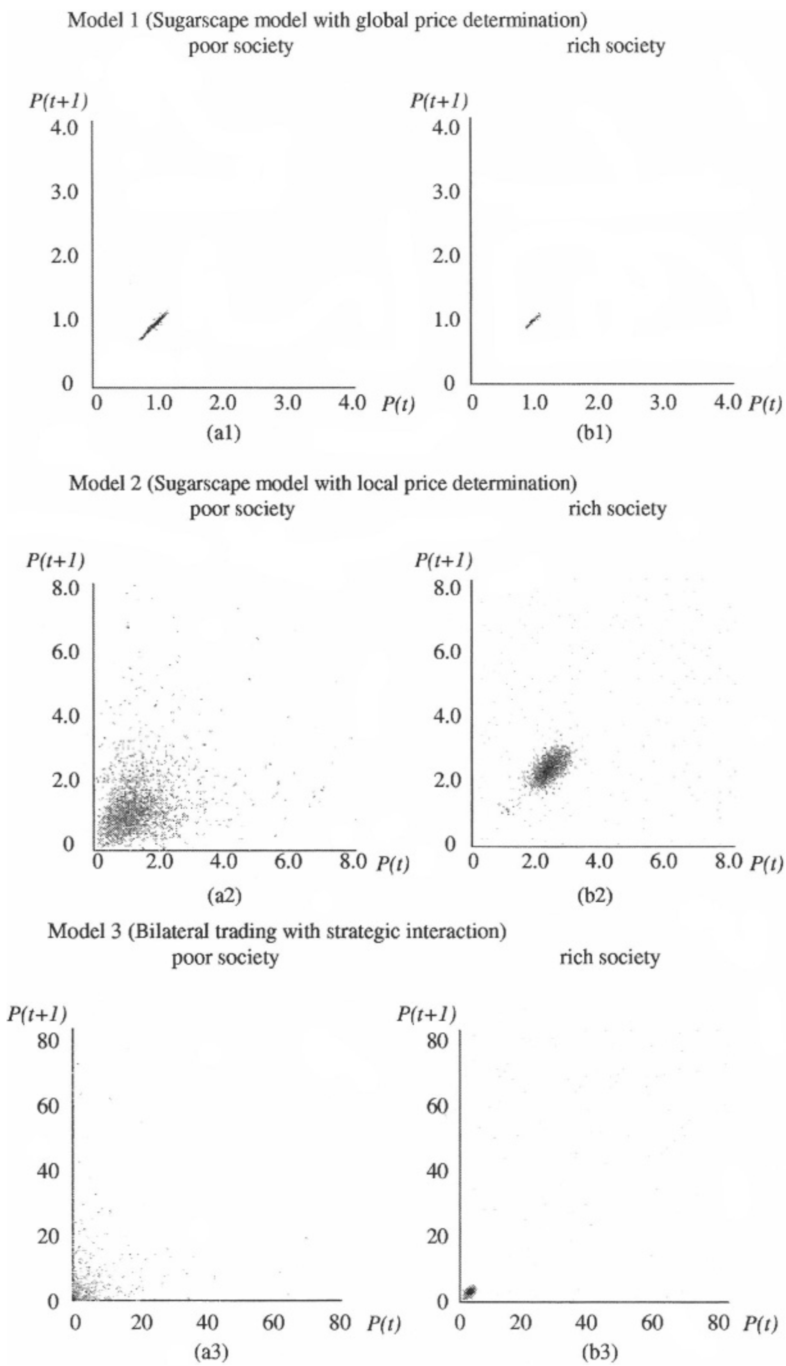

Fig. 3. The price dynamics under three models (the graph of $\boldsymbol{p_t}$ vs $\boldsymbol{p_{t+1}}$)

Table 2. The maximum value of the change

Model	Maximum value of the change	
	Poor society	Rich society
Global price	1.2	1.1
Local price without strategic interaction	10.9	3.5
Local price with strategic interaction	622.2	4.9

agents who were in demand for Food A are being satisfied, the price will drop. However, as time goes by, those agents who formally had an abundance of Food A are now having an abundance of Food B. They will thus demand more Food A. This new increase in demand for Food A will bring the price up again. This continuous cycle explains the invisible hand at work in allocating resources to agents in the market. The invisible hand brings about a stable market price by adjusting to the aggregate demand and supply in the market. The resultant price seeks to allocate resources to satisfy the demands of agents in the market. The result of this is a market price that fluctuates very little around the value of 1, which is the optimal price for it signifies that on the aggregate, all agents have equal demand for Food A and Food B.

From Fig. 3(a2), we can see that the prices in this model are fairly stable, and though there are fluctuations with time, these fluctuations are small. As for the local price model without strategic interaction, with average price close to the global market model, it implies that the local price model without strategic interaction can be a suitable candidate when the global market model cannot be implemented. To explain this, we can think of the local price model without strategic interaction as similar to the global market model but having a time lapse. Instead of the "magic auctioneer" obtaining the *MRS* of all agents in the market for each cycle and then setting the global price, the *MRS* of the agents are being transmitted to each other each time trade takes place, spreading across gradually the market. The agents, being free to move in the environment, will over time trade with a large proportion of the agent population, and thus the agent's resulting *MRS* would have been affected in a way similar to how the global price is affected by agents in the global market model. This implies that bilateral trade carried out at locally determined prices can bring about price stability without the need for some global magic auctioneer.

Prices in the local price model with strategic interaction fluctuate greatly in between cycles. Although the prices tend to remain low near the value of 10, there are times when prices soar to values above 100. The appearance of plots near the axes of Fig. 3(a3) shows that prices can differ greatly from cycle to cycle. The maximum value of the change in the local price model with strategic interaction is 622.2 and has a high average price, implying that it lacks price stability. The lack of limiting mechanisms results in prices moving far away from the equilibrium found in the global market model. Price stability is lost when agents use their bargaining power to affect the price for bilateral trade. Instead of a price that satisfies all agents in the society, or a price that benefits the trading partners equally, the trading price can now be biased towards one partner over the other. Due to the difference in bargaining power amongst agents, the trading price will vary greatly, resulting in great fluctuations in the trading price.

In the rich society, from Fig. 3(b1), (b2), (b3) and Table 2, we can see that all models can stabilize a price as compared to poor society. Especially, fluctuation in the local price model with strategic interaction is small dramatically in comparison with it of the poor society.

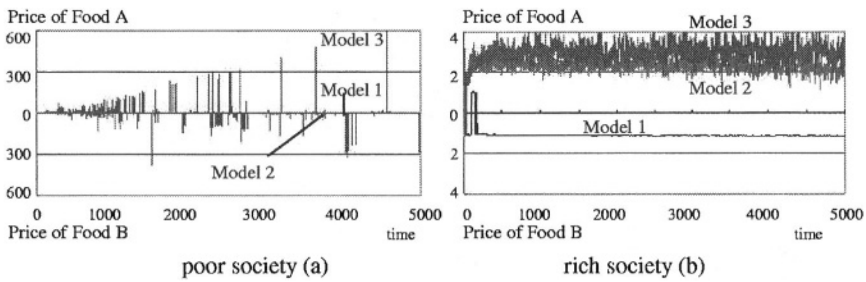

Fig. 4. The price dynamics (distance from the price of 1)

Fig. 4 shows a change in the price between Food A and Food B. The price of the Food A rises as much as to go to the top from 0. The price of the Food B rises as much as to go to the bottom from 0.

From Fig. 4(a), we can see that the global price and the local price without strategic interaction fluctuate very small and the local price with strategic interaction fluctuate greatly between the Food A and the Food B in the poor society.

On the other hand, from Fig. 4(b), we can see that the local price with and without strategic interaction lean to the Food A and the global price lean to Food B in the rich society. The price dynamics under the poor society is symmetrical as opposed to the price dynamics under the rich society is non-symmetrical.

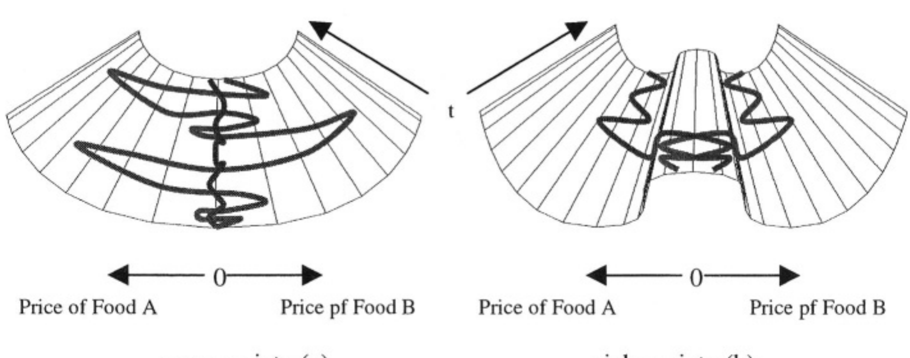

Fig. 5. The image of the price dynamics

It is easy to catch that think about the progress of the time with depth, and represent by bumpy surface. Fig. 5 is image of the price dynamics. We think that the poor society is wide concave surface and the rich society is narrow convexity surface. On the concave surface, the price fluctuates based on 0. On the convexity surface, early slight wobble lead the price either one side. On other words, Rock-in is caused in the rich society. It is a very interesting phenomenon.

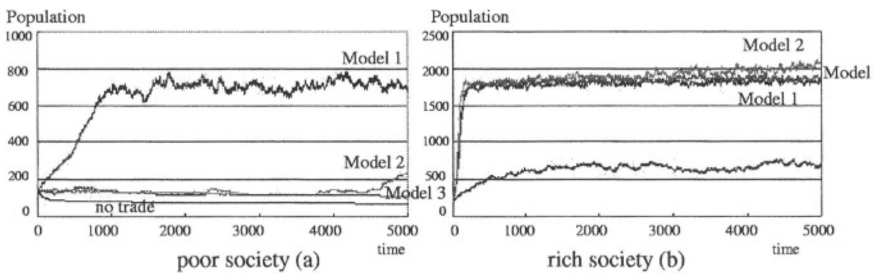

Fig. 6. Agent population over time (Survivability)

Next, we shall look at how the agent population changes with time. We shall see that trade allows the three trade models to support a larger agent population than the no trade model under the both society.

In the poor society, we shall see that the global market model is able to support a larger agent population than the local price models. In Fig. 6, we plot the change in agent population with time for all three models. We can see from Fig. 6(a) that the global price model is able to support the most number of agents. The two models using local prices are able to support a small number of agents. For the global market model, the number of agents increases and fluctuates around the value of 700. At the end of 5,000 cycles, agent population is 674. This is because after the initial death of "weak" agents, the remaining agents are able to move to regions in which they can get suitable amounts of both foods. New agents introduced into the market will be found in these regions too, thereby increasing their initial chances of survival. As the global price is stable and constant, trading attempts succeed easily. Thus, trade with existing agents in the region will also help these new agents to survive. As more and more agents are introduced into the area, chances for trade increase, and agents are able to get the foods they lack via trading with their neighbors. However, the average age at which agents die (i.e. the life expectancy of agents) is 77 cycles. The short lifespan of agents can be explained by overcrowding. As the number of agents increase, agents with a longer vision range will be able to seek out regions with high amounts of foods. Agents with shorter vision ranges will be forced to move into regions with less foods, and may ultimately die from starvation if their metabolic rates are high.

For the local price model without strategic interaction, there is an initial drop in agent population to the value of 140, after which the agent population fluctuates around the value of 140. Agent population at the end of 5,000 cycles is 240. Agents in the local price model without strategic interaction are able to live longer when compared with agents in the global market model. In this model, agents are able to live up to an average of 706 cycles before dying. This is because trading is now done at a price most beneficial to the agents involved. Thus, agents are able to live longer. However, while trading can succeed more easily since it benefits both agents equally, it can result in disastrous trading that leads to the death of new agents. Agents may trade away foods that they need. This explains why agent population stays low.

For the local price model with strategic interaction, the agent population drops to around 140 right from the beginning of the experiment, and fluctuates around 130or the remaining of the experiment. At the end of 5000 cycles, there are 110 agents remaining. Agents in the local price model with strategic interaction are able to live even longer when compared with agents in the local price model without strategic interaction. In this model, agents are able to live up to an average of 2071 cycles before dying. This is because trading is now done at a price most beneficial to "strong" agents involved. Thus, "strong" agents are able to live even longer than before. However, with stricter rules regarding trade, as well as the use of bargaining power, trade takes place less often, and thus some agents may not get enough foods and die from starvation. This is especially true for new agents introduced into the environment. This explains why agent population remains low. The results show how price determination affects the life expectancy of agents. A system designed to benefit the most agents, the global market model, results in a lower life expectancy, when compared to systems designed to benefit the individual agents, such as the two local price models. While a global price helps to allocate resources to more agents, it results in the agents living shorter lives. Local prices allow agents to accumulate resources for themselves, thus lengthening their lifespan.

In the rich society, we can see from Fig. 6(b) that all models are able to support a large agent population. For the all models, the agent population increases at a stretch to 1700 and maintained. The global price model, agents are able to live up to an average of 1769 cycles before dying. The local price model without strategic interaction's average is 1882 and the local price model with strategic interaction's average is 1806. In other words, each model can support a large agent population and long time.

This shows that trade increases the carrying capacity of the environment. It also shows that when trade is carried out in a manner beneficial to society, a high agent population can be achieved. All three trade models result in an agent population higher than that found in the no trade model, showing that trade helps an environment to support a large agent population.

3.2 Efficiency: The Average Utility

We compare how utility differs in the three models. We shall also look at the average utility per agent for each model in utility for agents in each model. The average utility for each of the three models is shown in Fig. 7.

In the poor society, from Fig. 7(a) we can see that average utility is highest amongst the trade models in the local price model with strategic interaction, though there are many fluctuations. At the end of 5,000 cycles, the average utility is 80. The model with the lowest level of average utility is the global market model, though it is fairly stable. The average utility at is 21 at the end of 5,000 cycles. The average utility for the local price model without strategic interaction is 22 at the end of 5,000 cycles.

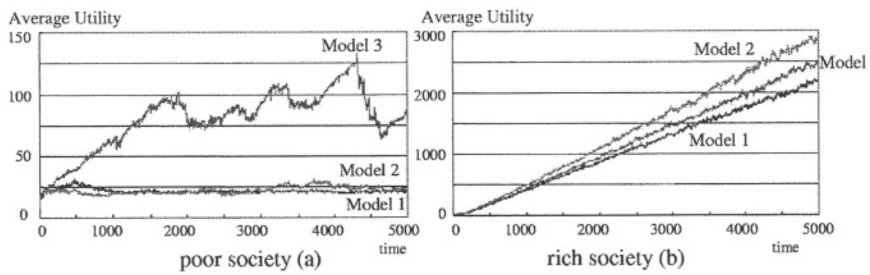

Fig. 7. Average utility over time

When we compare the utility of the trade models, it becomes clear that the global market model benefits society as a whole but not the individual. This implies that resources are equally distributed. This even distribution is a result of the invisible hand, which sets a global price such as to satisfy the demand of all agents. This is in contrast to the local price model without strategic interaction, which suffers from a low total utility but a level of average utility much higher than that found in the global market model. Agents in the local price model without strategic interaction are benefiting more than agents in the global market model. This uneven distribution results because agents seek to maximize their utility at a local level rather than at a global level. Finally, when strategic interaction is brought in, the individual and the society both benefits, as seen from the high total and average utility found in the local price model with strategic interaction. Local efficiency is being brought to its maximum. This also translates into a higher utility level on the global scale. However, the great fluctuation in utility implies that some agents are much better off than others, implying an unequal distribution of utility.

In the rich society, from Fig. 7(b) we can see that average utility of all models increase soaring. At the end of 5,000 cycles, the model without strategic interaction is 1405. The average utility for the local price model with strategic interaction is 1210. The average utility for the global market model is 1087. This ranking seems to have relations with the population.

4 Comparison of the Models

We compare three models in terms of stability, equity and efficiency under the poor society and the rich society. In the poor society, we shall see that the Sugarscape model with global market price is able to achieve the highest stability and equity, while with the local price is able to achieve a moderate level of stability and equity. The strategic trading model, on the other hand, is able to achieve the highest efficiency by forsaking stability and equity. In the rich society, the local price model without strategic interaction is the best, the local price model with strategic interaction is second and the global price model is the worst in all the comparative elements. So it is stated about the result under the poor society.

4.1 Stability

We can see that the Sugarscape with global price enjoys not just price stability, but from Fig. 7, we see that there is also stability in the level of utility. The invisible hand brings about a stable market price by adjusting to the aggregate demand and supply in the market. The resultant price seeks to allocate resources to satisfy the demands of agents in the market. The result of this is a market price that fluctuates very little around the value of 1, which is the optimal price. The local price model without strategic interaction enjoys a moderate level of stability in these areas as well. This implies that bilateral trade carried out at locally determined prices can bring about price stability without the need for some global magic auctioneer. The local price model with strategic interaction is unstable in price, utility and agent attributes. Instead of a price that satisfies all agents in the society, or a price that benefits the trading partners equally, the trading price can now be biased towards one partner over the other. Due to the difference in bargaining power amongst agents, the trading price will vary greatly, resulting in great fluctuations in the trading price.

4.2 Survivability

The global market model is able to support the most number of agents, while the no trade model can support the least. Agents in the local price model are able to live longer when compared with agents in the global market model. This is because trading is now done at a price most beneficial to the agents involved. Thus, agents are able to live longer. However, while trading can succeed more easily since it benefits both agents equally, it can result in disastrous trading that leads to the death of new agents. Agents may trade away foods that they need. This explains why agent population stays low.

Without trade, the agent population decreases with time. However, this decrease is not linear with time. At first, there is a significant decrease in the agent population. The rate of decrease slows down, after which few agents die. A system designed to benefit the most agents, the global market model, results in a lower life expectancy, when compared to systems designed to benefit the individual agents, such as the two local price models. While a global price helps to allocate resources to more agents, it results in the agents living shorter lives. Local prices allow agents to accumulate resources for themselves, thus lengthening their lifespan.

4.3 Efficiency

The local price model with strategic interaction is the most efficient model, both socially and individually. The global market model is able to realize a high level of social efficiency but lacks in individual efficiency. Due to this efficient allocation of resources, agents are able to introduce more new agents into the market. This results in an increase in the agent population. The local price model without strategic interaction is able to increase individual efficiency but results in a lower level of social efficiency. The agents involved in the bilateral trade will set a local price which benefits both of them equally, instead of a price that will benefit all agents in the environment. Local efficiency is obtained when the price of bilateral trade is set to satisfy the trading partners rather than to satisfy the whole society. In the local price model with strategic interaction, agents are able to maximize their utility through the use of their bargaining power, thus bringing local efficiency to an even higher level than that found in the local price model without strategic interaction. This higher level of local efficiency actually sums up to a higher level of global efficiency, much higher than that found in the global market model. Thus, the use of bargaining power can actually bring about both local and global efficiency.

4.4 Equity

The Sugarscape model with global price has a high level of equity. The invisible hand allocates resources so as to satisfy the demand of all agents in the market. As the demand of all agents are being satisfied more or less to the same degree, agents are just about as well off as their neighbors. The invisible hand is thus shown to be able to distribute resources in a fair manner. The local price model without strategic interaction is able to achieve a level of equity close to that found in the global market model. The lack of a global mechanism does not result in a lost of fairness in the society. Agents trading bilaterally using a locally determined price that benefits the trading partners equally are also able to maintain a moderate level of equity in the distribution of resources. The local price model with strategic interaction is lacking in equity. As agents now use their bargaining power to benefit themselves, resources are allocated away from agents with weak bargaining power towards agents with strong bargaining power. There is thus an uneven distribution of resources as agents with strong bargaining power are much better off than agents with weak bargaining power.

4.5 Summary

We sum up the above comparisons in Table 3.

Table 3. Comparison of Models

Society	Comparisons	Global Market Model	Local Price Model Without Strategic Interaction	Local Price Model With Strategic Interaction
Poor Society	Stability	◎	○	×
	Survivability	◎	×	×
	Efficiency	×	×	◎
	Equity	◎	○	×
Rich Society	Stability	◎	○	○
	Survivability	×	◎	○
	Efficiency	×	◎	○
	Equity	×	◎	○

(“◎” represents good, “○” means moderate, “×” means bad and)

5 Conclusion

In this paper, we looked at the characteristics of trading under conditions of a global market price and under conditions of local individual prices with and without strategic interaction. From our simulation results, we saw that bilateral trading without strategic interaction can obtain a market price close to that found in a global market Trade brings about greater equity. Trade also increases the carrying capacity of the environment, allowing more agents to survive. In effect, trade allocates resources towards needy agents so that more agents are able to survive. Agents who are in need of a resource are able to obtain those resources from other agents who have an abundance of the resource. Thus, agents who would otherwise starve to death can now live longer.

For the global market, the price is obtained from the demand, as determined by each individual's utility function. However, as individuals are free to move in the environment, under bilateral trading, when strategic interaction does not take place, this demand is communicated over time throughout the whole environment. It is similar to price determination in a global market with a time lapse. The third conclusion that we can draw from our results is that, when strategic interaction is introduced into bilateral trading, the price at which trading takes place is highly affected. Now, as individuals use the power that comes with possession of excessive amounts of a certain food, they are able to affect the trading price so as to benefit themselves. This is the model most close to a real world model, as monopolies set prices higher to reap more profits, and individuals will buy goods at different prices according to the urgency of their needs.

Especially, the global price model and the local price model with strategic interaction are the relation of trade-off in the poor society. In the rich society, the local price model without strategic interaction that no remarkable characteristics in the poor society is the best model. On the other words, a desirable model varies according to the environment.

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Monetary Policy and Banks' Loan Supply Rules to Harness Asset Bubbles and Crashes

Ichiro Takahashi[1] and Isamu Okada[2]

[1] Faculty of Economics, Soka University
1-236 Tangi, Hachioji City, Tokyo, 192-8577, Japan
itak@soka.ac.jp
[2] Faculty of Business Administration, Soka University
okada@soka.ac.jp

Abstract. By constructing an artificial micro economy including a central bank and a commercial bank, this paper attempts to examine strict decision-making in loan supply and bad loan management by private banks as well as the degree of monetary intervention by the central bank, and how this affects the emergence and collapse of asset bubbles. The virtual experiment demonstrates that the intervention is unnecessary if the commercial bank manage credit creation and nonperforming loans in a self-controlling way. Otherwise, the intervention is both welcoming and effective.

1 Introduction

Japanese has been facing an ailing economy, with seemingly insurmountable difficulties. One of the biggest, if not the gravest, problem is the surge in defaults and bad loans. The officially disclosed nonperforming loans amount to 40 trillion yen, approximately 30 billion dollars, as of September 30, 2002, according to Financial Services Agency[1]. Most of the Japanese banks are burdened with overwhelmingly enormous nonperforming loans, extended to the private sectors[2]amid the euphoria of the late 1980s.

Triggered by an extremely low rate of interest, the Japanese economy experienced the so-called "asset bubble" during the late 1980s. Stock and land prices had reached the all time high and Japanese people were confident about the strength of their economy. To suppress the abnormally soaring land price, the monetary authority restrained the loan supply of the commercial banks and sharply raised the discount rate, causing the bubble to burst and stock and real estate prices to plunge. As a result, the balance sheets of companies and individuals, as well as commercial banks, were greatly damaged, leading to discouraged investment and consumption. The accumulating bad loans caused inadequacy

[1] For more details, refer to the official home page of Financial Services Agency, http://www.fsa.go.jp/.
[2] The greater part of the bad loans are extended to service industry such as construction, real estate, and nonbank financial companies.

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of the bank's capital. The banks, unable to take risks, restricted credit creation activity, considered as one of the causes of the persistently ailing economy today.

There has been much recent interest in studing the banking problem in Japan. Cargil (2000) listed five factors that are responsible for it. Among these are the highly regulated financial system and enormous liquidity that the Bank of Japan created in the late 1980s and then abruptly eliminated. Ueda (2000) pointed out the failure of monetary policy that caused the large price bubble. By the regression analysis of Japanese banks, Hoshi (2001) showed that "the slow and incomplete deregulation of the financial system in the 1980s" made the Japanese banking sector more vulnerable to the wild swings in land prices.

By constructing an agent-based simulation model with trend chasing asset traders[3] and a single bank, Takahashi and Okada (2003) obtained the following results: 1) Healthy management of the banks is indispensable for a stable and sustainable economy; 2) For a healthy management, the banks must prepare adequate reserves against nonperforming loans and liquidate bad loans promptly, but not immediately.

This paper aims to answer the following question: if the banks had adopted restrictive loan supply policy, would the banking crisis in Japan have been avoided? We also address the question of what the appropriate monetary policy is for preventing the emergence of bubbles and facilitating the recovery after their bursts. Should it actively or inactively be involved in monetary intervention?

To serve these purposes, this paper extends Takahashi and Okada (2003) in two dimensions: first, a central bank is added to examine the effects of open market operations; second, the strictness in assessing the borrowers' credit limits is varied to examine how the bank loan supply rule affects the fluctuations of the land prices.

The simulation results attained in the paper are as follows: (1) the more restrictive loan supply policy the bank adopts, the more stable and sustainable the economy becomes; (2) the central bank's intervention in the financial market is likely to improve the performance of the economy if the commercial bank adopts a loose loan supply and nonperforming loans policy; (3) the intervention tends to be ineffective, or even harmful, if the commercial banks adopt stringent loan supply rule and prompt liquidation policy.

These results are consistent with the finding of Hoshi (2001). Hoshi (2001) argues that "the land price bubble alone, however, cannot explain the emergence of the problem in the Japanese banking sector" because "the bubble in the late 1980s was not the first in the postwar period, nor even the largest." Hoshi (2001) correctly pointed out "over-banking" as the fundamental problem, "which emerged when corporations shifted to capital market financing but options for savers and banks were extremely slow to be expanded."

Section 2 describes the agent-based model, Section 3 presents simulation results, and Section 4 discusses the results. Section 5 gives conclusions and future extensions.

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[3] Steiglitz and Shapiro (1996) showed that price bubbles and subsequent crashes occur when fundamentalists and trend chasers are both present.

2 Model

We consider a small country consisting of many consumers, one commercial bank, and a central bank. There exists a foreign country, but no government, implying existence of neither tax nor government expenditure. There are two kinds of inputs: land and labor. A consumer sells and buys land in an asset market. These inputs produce a fixed amount of composite consumption commodity. The consumption commodity is perishable with exogenously determined price at unity[4]. There exists also fiat money (cash), which is always convertible with single unit of consumption commodity. The consumers and the banks use fiat money to facilitate asset transactions as well as to store values. The consumer determines the demand for fiat money and the consumption commodity. In general, the supply of and demand for the consumption commodity do not balance. This form of trade imbalance is financed by a cash flow. The bank accepts deposits from and lends funds to the consumers for their investment activity. In addition, there is another kind of financial assets, or national bonds held by the bank. To avoid unnecessary complications, the maturity periods for deposits, loans and national bonds are assumed to be infinity and the rate of interests applied to them to be variable. The central bank occasionally conducts open market operation by selling and buying national bonds held by the commercial bank.

Moreover, time is discrete and the economy continues until period T ($t = 1, 2, \ldots, T$). In each period, the real estate and financial markets open and transactions of land and funds are made, revising the land price and the interest rate.

2.1 Consumers

There are N consumers in this economy, all engaging in selling and buying land in the real estate market. Consumer i owns L_t^i units of land in time t. She is a landlord when $L_t^i \geq 1$, and a worker when $L_t^i = 0$.

For expositional convenience, the consumption goods produced by one unit of land is referred to as rent and those produced by a worker as wage. Assume also that land here is combined with a building so that a landlord serves as a manager of the building[5]. There are increasing returns to scale in building management so that one landlord can manage any number of lots of land. Generally, there involves a huge uncertainty in running rental offices: for example, whether or not the building can attract a sufficient number of tenants, and the extent of rent fluctuations. For our purposes, we can ignore these uncertain factors. That is, each lot can find a tenant with probability one and the rent R_t in period t

[4] The world price of the consumption commodity is one, which is taken as given by the small country assumption.

[5] Land can be thought of as capital stock that is nonproduceable and nondepreciable. For example, imagine an extremely long-lived building and/or numerically controlled machine which was already constructed or built. All the lands and labors are assumed to be homogeneous.

is exogenously given as a constant. In notation, $R_t = R$, $(t = 1, 2, \ldots, T)$. A worker earns exogenously given wage, W[6].

Each consumer possesses at time t, bank deposit, DP_t^i, and fiat money, F_t^i as assets. Then, a negative value of DP^i implies that the consumer has borrowed a loan of absolute value of DP^i dollars from the bank. For ease of exposition, the consumer is not allowed to buy national bonds. Selling one lot of land involves a fixed transaction cost, denoted by C_L, such as a charge by a real estate agency and income taxes. A landlord revises the disposable value of the lots she owns, AS_t^i, as

$$AS_t^i = (P_t - C_L)L_t^i, \tag{1}$$

where P_t represents the market price of land. Net equity of Consumer i is given by

$$E_t^i = DP_t^i + F_t^i + AS_t^i. \tag{2}$$

This gives the equity ratio of Consumer i as $ER^i = \frac{E^i}{AS^i + \max(DP^i, 0) + F^i}$.

The balance sheet of a consumer with positive bank deposition $DP > 0$ becomes:

Table 1. Balance Sheet of Consumer with positive DP

Assets	Liabilities+Equity
Land (AS) Bank Deposit (DP) Fiat Money (F)	Equity (E)
Total (AS+DP+F)	Total (E)

The balance sheet of consumers who has borrowed from bank $(DP < 0)$:

Table 2. Balance Sheet of Consumer with negative DP

Assets	Liabilities+Equity
Land (AS) Fiat Money (F)	Loan Outstanding (-DP) Equity (E)
Total (AS+F)	Total (-DP+E)

The value of equity can be negative for this case. A consumer receives interest income or makes interest payment depending on whether her bank account is positive or negative. Let r^d denote the rate of interest on deposit and that of loan by r^ℓ. Net interest income of Consumer i, I^i, is given by

$$I_t^i(DP_t^i) = \begin{cases} r^\ell DP_t^i & \text{for } DP_t^i < 0 \\ r^d DP_t^i & \text{for } DP_t^i \geq 0. \end{cases} \tag{3}$$

[6] Endogenizing R and W is likely to unstabilize the economy. To concentrate on the issue of controlling the land price and the interest rate, these variables are treated as exogenous

Thus, the income of Consumer i in period t, Y_t^i, depends on the number of lots she owns and the amount of deposit or loan outstanding. This is shown as

$$Y_t^i(L_t^i, DP_t^i) = \begin{cases} W_t + I_t^i(DP_t^i) & \text{for } L_t^i = 0 \\ R \times L_t^i + I_t^i(DP_t^i) & \text{for } L_t^i \geq 1. \end{cases} \tag{4}$$

As her income revises, so does her equity, and these two variables, in turn, determine the demand for cash holding, F_t^i. The demand for cash holding positively depends on current income and equity, and inversely relates with the interest rate on deposit. The consumer needs to hold at least F_{min} dollars and hold α_f^y and β_f^y dollars as cash out of additional one dollar of income and net wealth respectively. Specifically, the demand function of cash holding is given by

$$F_t^i(Y_t^i, E_t^i) = \max(F_{min}, \frac{\alpha_f^y Y_t^i + \beta_f^e E_t^i}{r_t^d}). \tag{5}$$

Subtracting cash holding, brought forward from the previous period, from the current demand for cash is denoted by ΔF_t^i. In what follows, whenever obvious, $\Delta X_t \equiv X_t - X_{t-1}$. Whatever remains of current income after paying for current consumption expenditure and net change in cash holding, ΔF_t^i, or $Y_t^i - C_t^i - \Delta F_t^i$ is added to her bank deposit. Of course, if this remainder is negative, deposit decreases by the same amount or loan increases depending on the level of the deposit outstanding at the end of the previous period.

There is an autonomous level of consumption, C_{min}, to sustain the minimum level of livelihood. Generally, consumption level C_t^i positively depends on both income and equity, and shows downward rigidity. We assume here that if the target level of consumption, C_t^*, exceeds the previous level of consumption, the consumer immediately materializes this target value. On the other hand, if the target value falls short of the previous realized level, the consumer gradually adjusts actual consumption level towards the target. Denoting the speed of adjustment by π_c,

$$C_t = \begin{cases} C_t^* & \text{for } C_{t-1} < C_t^* \\ C_{t-1} + \pi_c(C_t^* - C_{t-1}) & \text{otherwise.} \end{cases} \tag{6}$$

The target level of consumption is assumed to depend on the permanent income, Y_t^p, and net wealth, E_t[7]. Thus, using obvious parameters,

$$C_t^* = \max(C_{min}, \alpha_c^y Y_t^p + \beta_c^e E_t), \tag{7}$$

where α_c^y denote and β_c^e denote marginal propensities to consume out of income and net wealth, respectively.

As will be stated later, a consumer engages in transaction of land. Settlement of payment is done through deposit accounts of the buyer and the seller. In other words, cash is exclusively used for current transactions and not for asset transactions.

[7] Y_t^p is computed as the average income over last H periods, which represents the length of memory of the consumer.

2.2 A Commercial Bank

For simplicity, we assume that there is a single bank in this artificial economy. The model captures two channels of monetary policy transmission: the "interest rate" and "credit" channels. Through the interest rate channel, a monetary policy leading to a change in real interest rates, which in turn alters the cost of capital, thereby affecting investment spending. Credit channel itself includes the bank lending channel and the balance-sheet channel. For detailed theoretical and empirical discussion related to monetary policy transmission and bank lending supply, refer to Mishkin (1995), Kashyap and Stein (1994), and Bernake and Gertler (1995).

The rate of interest changes according to the supply of and demand for funds in the financial market. Although the bank is a monopolist, it takes the interest rate as given. The difference between loan rate and deposit rate is exogenously fixed as d by governmental regulation. The bank incurs fixed running cost C^b every period. The bank has national bonds denoted by B^b, earning interest income. The bank passively responds to sales or purchases by the central bank and does not sell or buy bonds on its own initiative[8].

For later reference, let $I = \{1, 2, \ldots, N+1\}$ denote the set of all agents ,i.e., all the consumers and one bank with $(N+1)$st agent as a bank.

The balance sheet for the bank appears as:

Table 3. Balance Sheet of Bank

Assets	Liabilities+Capital
Loan Outstanding (B) Land (AS) National Bonds (B^b) Vault Cash (VC)	Deposit Outstanding (DP^b) Loan from Central Bank (DT) Capital (E)
Total ($B + AS + B^b + VC$)	Total ($DP^b + DT + E$)

The bank establishes a credit limit for each consumer, $\bar{DP}^i_t$, depending on the net wealth and income level of the consumer. Credit limit also depends on the financial condition of the bank itself. A bank with adequate capital is willing to take risks while a bank with inadequate capital becomes reluctant to lend fund. This is the so-called "restricted lending" problem. In an extreme case, the bank forces consumers to pay back the loan[9]. The level of loan affordability is denoted by $A^b_t \in [0, 1]$. A^b_t is the function of capital ratio of the bank and takes on value zero if the capital ratio, ER^b_t, stays below ER^b_{min} and takes on value one if it is above ER^b_{max}. Specifically, the loan affordability is given by

[8] This assumption needs to be made because the market is too thin.

[9] As will be seen later, if it becomes apparent that the level of loan of a debtor reaches her upper limit, the bank forces the debtor to sell the property to collect the money it has lent.

$$A_t^b(ER_t^b) = \begin{cases} 0 & \text{for } ER_t^b < ER_{min}^b \\ \frac{ER_t^b - ER_{min}^b}{ER_{max}^b - ER_{min}^b} & \text{for } ER_{min}^b \le ER_t^b < E_{max}^b \\ 1 & \text{for } ER_t^b \ge ER_{max}^b. \end{cases} \tag{8}$$

The bank sets up the upper bound of the loan for each individual and updates it every period according to

$$\bar{DP}_t^i = -\alpha_{dp}^a A_t^b(ER_t^b)(\beta_{dp}^y Y_t^i + E_t^i). \tag{9}$$

α_{dp}^a is a control variable of the bank, signifying the strictness in assessing the borrower's credibility[10]. For harnessing bubbles, it will turn out that this variable is crucially important. β_{dp}^y represents the extent to which the bank assesses the annual income of the prospective borrower.

The bank usually determines the due date for a loan. For computational ease, we assume that the bank receives interest payment from a debtor and as long as the debtor makes interest payment by the due date and her amount of loan outstanding is under her credit limit, the bank does not demand the reimbursement of the loan. In Japan, facing huge amount of loan outstanding, a bank considers it to be too big to fail. Hoping the economy picks up and the loan outstanding diminishes in size, the bank continues to loan out even the unpaid interest payment for the distressed debtor. To capture this situation called "forbearance," the bank is assumed to dispose nonperforming loan which pays the interest overdue differently according to the size of the loan. If the amount of claim outstanding is smaller than the exogenously fixed level, *CUT,* the bank extends due date up to three periods. However, it will liquidate the claim if she fails to pay four periods in a row. If the debt exceeds the *CUT* level, the bank multiplies the amount of claim by 1 – *WR* to get the substantial amount of the claim, used to calculate the capital ratio[11]. Moreover, banks must decide when to liquidate the claim against borrowers who fail to return the loans[12]. We denote, by *SUR,* the number of the periods the bank allows the distressed borrower to survive before liquidation. If the bank fails to liquidate the nonperforming loan and forbears it too long, it may expand unlimitedly so that it will swallow a huge fund, taking away necessary fund from healthy prospective borrowers. Moreover, forbearance will incur a downside risk of decreased liquidation value due to the continuously declining land price. On the other hand, early liquidation may deprive the borrower of the chance to get over the financial difficulty[13].

[10] Japan's banks often required collateral for loans to view customers. In the late 1980s, many Japan's banks considered land as the most secure collateral and overestimated the collateral value, which is captured as large α_{dp}^a.

[11] This corresponds to indirect write-off. A bank makes loss reserves against seriously distressed borrowers according to the borrowers' risk. The claim outstanding minus loss reserves corresponds to the substantial claims. Here, nonperforming loan multiplied by *WR* corresponds to the loss reserves.

[12] Liquidation here is equivalent to direct write-off. It means to confiscate to cash and land possessed by the debtor and to sell the land in the asset market

[13] There has been much recent interest in studying the rationales of banks' behavior of forbearance after the bubble burst. Employing the real options approach, Baba

The rate of interest moves in accordance with the excess demand for the fund. The newly created fund that can be used for lending is the increase in vault cash, *VC,* held by the bank net of the reserves for new deposit[14]. Newly created demand for fund is the new lending. Therefore, this flow gap causes fluctuations of the interest rate. However, the interest rate reflects the expected rates of the market traders. In forming expectations, they may take the past history of the expected demand into account. To model this dependence on the past excess demand, the interest rate is assumed to depend not only on the current level of excess demand but also on the cumulative excess demand for funds. The ratio that depends on the past cumulative flows is represented by ω_B.

$$EXF_t = B_t - (VC_t - rvDP_t) \tag{10}$$

$$CEX_t = (1 - \omega_B)\Delta EXF_t + \omega_B CEX_{t-1}, \tag{11}$$

where

$$CEX_0 = (1 - \omega_B)\Delta EXF_0. \tag{12}$$

$$r_t^d = \max(\min(\gamma, CEX_t), -\gamma) \tag{13}$$

The last equation reflects the assumption that the rate of interest moves at most at γ, regardless of the magnitude of the gap between supply and demand[15].

2.3 Supply of and Demand for Land

The supply of and demand for land is generally determined by how attractive the land is relative to financial assets. In each period, a landlord is allowed to sell only one lot of land. The bank obtains land whenever it liquidates collateral for the nonperforming loan. After transferring the ownership of the collateral by directly writing off the bad loan, the bank always tries to sell all the lots it owns.

A landlord attempts to sell one unit of land when her balance sheet is badly damaged due to insufficient income or expected decline in the land price, represented as follows:

$$DP_t^i + \min(0, Y_t^i) - L_t^i \max(0, P_{t-t_a} - P_{t-1}) < \bar{DP}_t^i. \tag{14}$$

(2001) derived optimal timing in banks' write-off decisions: "a very large rate of reinvestment return is required for the banks to immediately write off their nonperforming loans." Kobayashi and Inaba (2002) theoretically rationalized the forbearance of the banks from "a coordination failure in the network of the division of labor."

[14] The required deposit reserves is the amount of deposits multiplied by reserve ratio, rv. Vault cash increases as the bank gets new deposit.

[15] The difference ΔEXF_t represents the difference between newly created demand for and newly created supply of funds, i.e., the flow of excess demand. Simple computation reveals the above equation can be rewritten as $CEX_{t-i} = (1 - \omega_B)\sum_{i=0}^{t}(\omega_B^i \Delta EXF_{t-i})$. We can interpret it as the normalized excess demand, perceived by the traders, which influences the interest rate. In this interpretation, ω_B signifies the rate of forgetness.

The second term on the left side signifies the negative income, the third term, the capital loss. This rule can be interpreted as a reaction to bank's demand for collecting the existing loan, or as a defensive behavior of the landlord.

Let $\tilde{\theta}$ denote a random variable uniformly distributed between an interval [0, 1]. For consumer i, the attractiveness of land in period t, denoted by x_t^i, is given by

$$x_t^i = y_t^i + (2\delta_1\tilde{\theta} - \delta) - r_t^\ell, \tag{15}$$

where

$$y_t^i = \frac{R_t + \delta_2\tilde{\theta}(P_{t-t_a} - P_{t-1})}{P_{t-1}}. \tag{16}$$

The first term on the right hand side of equation (16) represents rent income accrued from owning one unit of land. The second term captures the expected capital gain perceived by the trend chasers augmented by δ_2, the strength of the trend chasing attribute. For various reasons, a necessity to demand either the sale or the purchase of land arises. The second term of equation (15), $(2\delta_1\tilde{\theta}-\delta_1)$, represents such a factor, influencing the sales or purchase decisions. These gains from holding land, minus loan interest denoted by the third term, measures the net marginal gain from possessing one additional unit of land. The expected capital gain in equation (16) reflects the change in land price over the last (t_a-1) periods. Even though all the traders are trend chasers, the capital gain term is weighed by a random variable, $\tilde{\theta}$, to capture divergent expectations among traders. Sometimes, people expect the trend to intensify and in other times, they foresee the trend to be damped. The second term, $(2\delta_1\tilde{\theta} - \delta_1)$, also helps traders form different expectations. When the landlord judges the land to be less attractive, i.e., less than x^s, or her net wealth ratio is too low, i.e., less than ER^s, she will attempt to sell one unit of land. For i such that $L_t^i \geq 1$, the supply of land, S_t^i, is

$$S_t^i(x_t^i) = \begin{cases} 1 & \text{if } x_t^i < x^s \text{ or } ER_t^i < ER^s \\ 0 & \text{otherwise.} \end{cases} \tag{17}$$

A landlord or worker, unless she is a debtor of nonperforming loan, will try to make a purchase of one unit of land if having the additional unit is attractive enough, that is larger than x^b, and has a sufficient level of deposit. The demand for land for consumer i, denoted by D_t^i, is expressed as

$$D_t^i(x_t^i) = \begin{cases} 1 & \text{if } x_t^i > x^b \text{ and } DP_t^i - (1+\delta_d\tilde{\theta})P_t + Y_t^i - C_t^i > \bar{DP}_t^i \\ 0 & \text{otherwise.} \end{cases} \tag{18}$$

Supply and demand meet randomly in the asset market, resulting in transactions. The short side of supply and demand determines actual quantity of traded units. Prospective traders on the long side of the market are randomly selected to meet a trader on the opposite side to complete the transaction.

In general, the prices of real estate are sticky. The price responds to the difference between supply and demand. Let π^L denote the speed of adjustment. As in the case of the interest rate, the land price reflects not only the current excess demand, G, but also, the cumulative excess demand up to the previous periods, CG[16]. Parameter, ω_L, denotes the ratio representing a part of the moving prices which depends on the past cumulative excess demand. The weighed excess demand is

$$CG_t = \omega_L CG_t + (1 - \omega_L)G_t, \tag{19}$$

where

$$G_t = P_t \frac{\sum_{i\in I} D_t^i - \sum_{i\in I} S_t^i}{\max(\sum_{i\in I} D_t^i, \sum_{i\in I} S_t^i)}, \text{ and} \tag{20}$$

$$P_t = \pi^L CG_t + P_{t-1}. \tag{21}$$

2.4 The Central Bank and Monetary Policy

The central bank should decide when to conduct selling or buying operation. When it conducts market operations, exogenously fixed amount, $\bar{B}$ dollars worth of bonds are transacted with the commercial bank in exchange for its vault cash.

Observing the fluctuating land price, the central bank absorbs vault cash by selling operation if the land price is on the rise and above the predetermined level P^s. It stops the operation when one of the conditions does not hold any more. Similarly, buying operation starts when the land price falls below P^b and continues until the price hits the bottom.

$$B_t^b = \begin{cases} B_{t-1}^b + \bar{B} & \text{if } P_t < P^b \text{ and } P_t < P_{t-1} \\ B_{t-1}^b - \bar{B} & \text{if } P_t > P^s \text{ and } P_t > P_{t-1} \\ B_{t-1}^b & \text{otherwise.} \end{cases} \tag{22}$$

2.5 Income Redistribution

The economy installs the income redistribution mechanism to avoid excessive concentration of wealth into a handful of landlords. Whenever liquidated debtors exit the economy, one rich landlord is randomly selected among those who posses more than three lots. One third of the lots owned by the chosen landlord is confiscated and given away to entrants who replace the bankrupt landlords[17]. If there are more entrants than the number of the lots available, the lucky entrants will be randomly selected.

[16] Another interpretation is plausible. In the land market, characterized as monopolistic competition, a seller adjusts the price gradually based on the history of the past land prices.

[17] For more realistic story, consider that spaces become available after the debtors exit form the economy for a rich person to raise kids. The rich landlord gives one third of her property to her children collectively and one unit for each child.

3 Simulation

3.1 Initial Setting

In order to make the artificial society as stable and equitable as possible, each consumer initially possesses one unit of land, i.e., $L_0^i = 1$ for each i. Initially, deposits outstanding, or DP_0^i, were set as uniformly distributed between \$ – 2000 and \$2000. Moreover, the values for other initial parameters are Table 4.

Table 4. Initial Parameters

N	100	L_t^i	1	P_0	8000	R	1000	W	500
C_L	200	FT_0	1000	r_0^ℓ	0.07	r_0^d	0.06	F_{max}	5000
F_{min}	500	α_f^y	0.05	β_f^e	0.001	C_{min}	600	C_0	1000
H	10	Y_i	$1000, (i = 0, -1, \ldots, -9)$	π_c	0.1	Y_0^p	1000	L_0^{MBR}	0
α_c^y	0.95	β_c^e	0.01	d	0.01	C^b	5000	B^b	0
VC_0	700000	DT	200000	ER_{min}	0.03	ER_{max}	0.25	β_{dp}^y	3
CUT	−5000	WR	1.0	rv	0.0	CEX_0	0	EXF_0	0
ω_B	0.5	γ	0.003	t_a	4	$\bar{B}$	10000	y_0^i	0.1
δ_1	0.2	δ_2	1	ER^s	0.3	x^s	0.01	x^b	0.03
δ_d	0.5	π^L	0.1	G_0	0	CG_0	0	ω_L	0.5

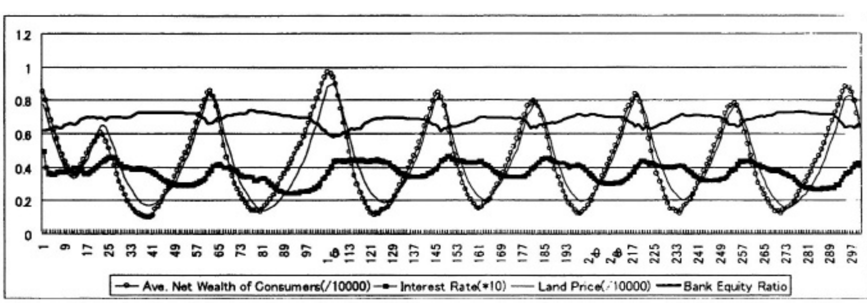

Fig. 1. A sample trend as $\alpha_{dp}^a = 0.6$

3.2 Simulation Results

Setting $T = 300$, $SUR = 10$, and $\alpha_{dp}^a = 0.6$, Figure 1 shows a sample trend of the land price, the rate of interest, average net wealth of consumers, and the bank's capital ratio when there is no market intervention by the central bank.

Figure 2 shows the trend of the same variables with the same parameter set in Figure 1, except for $\alpha_{dp}^a = 0.9$. The open market operations are added to the case shown by Figure 2 with values of $P^b = 3950$ and $P^s = 7500$, which is shown in Figure 3.

Furthermore, single simulation was conducted for 300 periods and 100 simulations were made with various random seeds. If the central bank conducts buying operations more frequently than selling operations, then monetary base is injected into the economy. To remove the change in money supply, the combinations of P^b and P^s that give the same number of periods of either operations were found and listed in Table 5. A pair of high P^b and low P^s represents a cautious intervention while a pair of low P^b and high P^s represents an active intervention. Figure 4 shows the effect of the degree of central bank interventions and its effects on the commercial banks performance in four cases: the number of simulations, in which the bank survives throughout the entire 300 simulation periods, is plotted, against the degree of intervention, measured by the frequency of market operations, for different parameter values of *SUR* and α^a_{dp}, i.e., *SUR* = {3, 10}, and $\alpha^a_{dp} = \{0.6, 0.9\}$.

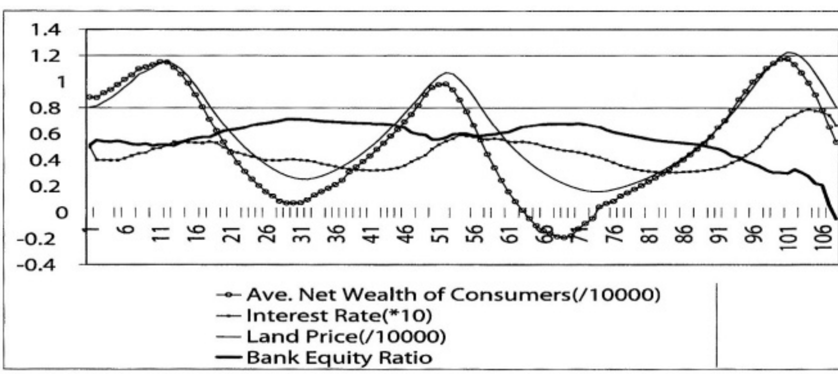

Fig. 2. A sample trend as $\alpha^a_{dp} = 0.9$ with no intervention

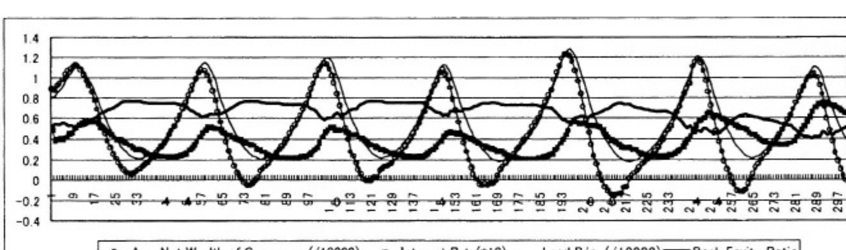

Fig. 3. A sample trend as $\alpha^a_{dp} = 0.9$ with intervention

Table 5. Combination of P^b and P^s and Rate of Central Bank Intervention

P^s	P^b	Rate of Intervention(%)	P^s	P^b	Rate of Intervention(%)
9500	1000	0.0	6500	2600	25.3
9000	1600	2.0	6000	2800	30.0
8500	1800	4.7	5500	3000	34.7
8000	2000	9.3	5000	3200	39.3
7500	2200	14.7	4500	3400	44.7
7000	2400	20.0	4000	3600	48.7

Note: $\{SUR, \alpha^a_{dp}\} = \{3, 0.6\}$

We selected two cases as good performers: $\{SUR, \alpha^a_{dp}\} = \{3, 0.6\}$ and $\{SUR, \alpha^a_{dp}\} = \{3, 0.9\}$. Figure 5 shows how many consumers went bankrupt each period on average for these two cases.

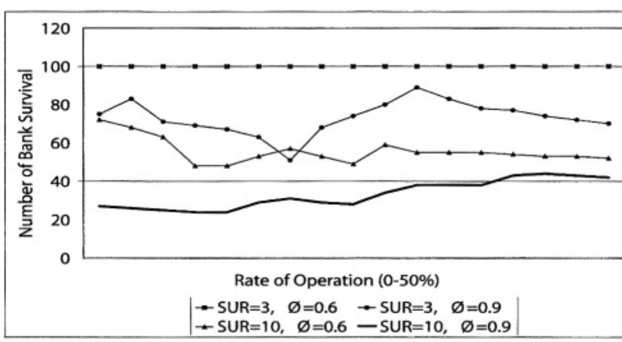

Fig. 4. A degree of central bank interventions and its effects on the commercial banks performance in four cases

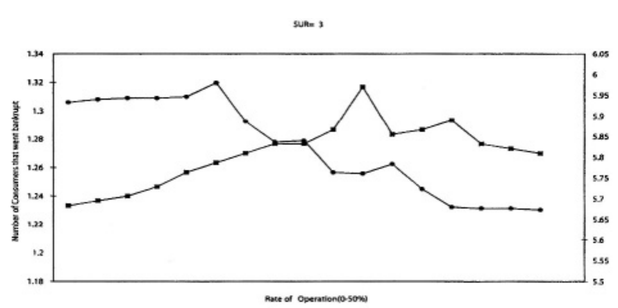

Fig. 5. How many consumers went bankrupt each period on average for two cases

4 Discussion

Figure 6 graphs the data for land prices[18] and real interest rates of Japan from 1979 to 2002[19], which were found to be consistent with their simulated trends derived in Figure 1, 2 and 3.

The agent-based model presented in this paper successfully captures the emergence and burst of the asset bubbles. Figures 1, 2, and 3 demonstrate that the artificial economy gives rise to asset bubbles and their bursts. Because all the traders in the asset market are trend chasers, a small fluctuation of the land price is likely to grow as a full-fledged bubble. Rising land price induces consumers to borrow fund from the bank to finance the purchase of land. The increased demand supported by expanded credit, in turn, raises the interest rate as well as the land price. Eventually, purchasing land becomes non-profitable because both the land price and the opportunity cost of land, reflected by the interest rate, reach the ceiling. As a result, the trend is reversed and land prices plunge. This bubble burst induces landlords, attempting to restore the balance in their damaged balance sheets, to sell their land. Because the majority of traders behave similarly, the land price falls further. The crumbling economy finally observes debtors who fail to make interest payment. Thus, the bank must face the non-performing loans. Liquidating collateral for bad loan forces the debtors to exit from the economy.

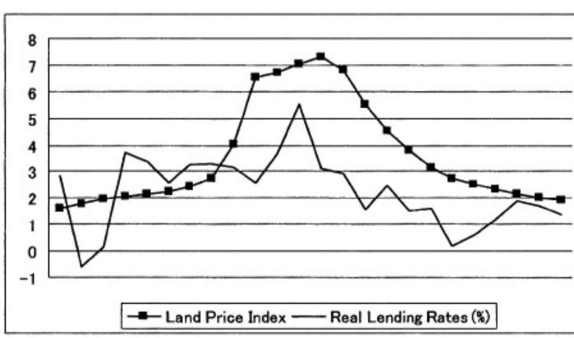

Fig. 6. Trends in Land Prices in Tokyo Commercial Area and Real Interest Rates in Japan (1979-2002)

[18] The land prices are indices for Tokyo commercial area with 1971 as the base year, calculated from the data released by the Ministry of Land, Infrastructure and Transport, Japan.

[19] The real interest rates are calculated by subtracting the change in consumer price index (Statistics Bureau, Ministry of Public Management, Japan) from the prime short-term lending rates at the end of year (Bank of Japan Statistics and Other Key Statistics).

According to the virtual experiments we have conducted, more cautious loan activity tends to lead to more sustainable economy with fewer defaults in both banking and private sectors due to less volatility in the asset market. The ceiling of either the land price or the interest rate is lower and the bottom is higher in Figure 1 than in Figure 2. The more cautious loan supply policy yields less volatile movement of the land price, which causes fewer bankruptcies. When the commercial bank is less cautious the moderately active central bank is likely to stabilize the economy. Figure 3 demonstrates the efficacy of open market operations: they suppress the magnitude of the land price fluctuations, thus deterring the default of the bank.

The lower peak price of land due to restrictive credit expansion implies the smaller capital loss after the bubble burst, thus less frequent liquidations. Even if liquidation occurs, the bank incurs smaller loss due to the conservative collateral assessment.

Figure 4 shows that the more strictly the bank supplies loans and liquidate nonperforming loans, the higher performance the bank achieves. Regardless of the level of monetary activeness, $\{SUR, \alpha_{dp}^{a}\} = \{3, 0.6\}$ is the best performer in terms of the likelihood of the bank survival. $\{SUR, \alpha_{dp}^{a}\} = \{3, 0.9\}$ is ranked as the second, $\{SUR, \alpha_{dp}^{a}\} = \{10, 0.6\}$ as the third, and $\{SUR, \alpha_{dp}^{a}\} = \{10, 0.9\}$ as the worst.

The incidents of direct liquidation increases soon after a bubble bursts. Even in the period of declining land price there is still significant size of demand. With three periods as SUR, she is allowed by the bank to sell her land to pay back the loan for three periods. The longer the bank waits, the larger the probability that the distressed borrower can sell her land. In typical cases, the probability of successfully selling her property during the three periods is more than a half. But waiting is costly because of the downside risk discussed above. It seems that the marginal benefit equals the marginal loss when SUR is around 3. In real world, banks have to compare these benefit and loss in determining the length of SUR.

According to Figure 4, if the bank behaves with strict self-discipline, i.e., $SUR = 3$ and $\alpha_{dp}^{a} = 0.6$, there seems to be not much room for monetary policy. In all the simulations, the bank successfully survives if the central bank conducts virtually no open market operation. Figure 5 suggests that the intervention, actually, hurts the economy for this case. Inspection of these figures also reveals that the more active intervention tends to raise the performance of the economy as the commercial bank adopts looser loan supply and bad loan policies.

5 Concluding Remarks

According to the virtual experiment we conducted, monetary intervention appears unnecessary if the commercial bank runs itself carefully. This result confirms a conventional wisdom: "Freedom under self-discipline does not require intervention."

The failure of monetary policy is to be blamed for having created and crashed the large land price bubble in the late 1980s. Our simulation results, however, argue that the bubble would not have arisen if the commercial banks had adopted restrictive lending policy. This conclusion is consistent with the one obtained by Hoshi (2001). His findings are based on thorough empirical research while ours are on agent-based simulation. The advantage of the current work is that it enables us to observe the processes of the rise and collapse of asset bubbles, and thereby to understand the mechanism of monetary policy transmission.

If the commercial bank adopts loose loan policy, active intervention can enhance the performance of the economy. However, we should regard this statement with caution. According to Ellison and Valla (1999), an active monetary policy, by producing more information, helps private agents to learn and adjust their expectations faster, thus creating extra volatility.

Future extensions are in order. The number of commercial banks will be increased to capture more realistic financial market and to examine the effect of banks' profitability on the economy. In addition, to incorporate the strategic interaction between policy maker and agents, both the consumer agents and bank agents must be capable of learning. These extensions, together with inverse simulation techniques [Terano and Kurahashi, 1999], will further shed light on a number of issues concerning the loan supply rules of the commercial banks and the appropriate policy of the monetary authority.

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Social Change: Exploring Design Influence

Ricardo Sosa and John S. Gero

Key Centre of Design Computing and Cognition
School of Architecture, Design Science and Planning
University of Sydney, NSW 2006, Australia
{rsos7705, john}@arch.usyd.edu.au

Abstract. This paper explores some aspects of group divergence based on principles relative to design disciplines. Extensions to an elementary model are used to explore the relation between divergence and social influence mechanisms previously employed to explain group convergence. The emergence of change agency is investigated.

1 Design Disciplines and Social Change

Social influence has been addressed in agent-based systems from a variety of viewpoints [1–8]. A predominant approach focuses on aspects related to convergence phenomena and in particular to the emergence of social groups or communities of individuals that develop shared characteristics from their interaction. Design disciplines like architecture and industrial design benefit from findings related to the dissemination of values throughout a population of agents. Experiments with the formation of social groups illustrate the fundamental processes by which a particular solution -a design artifact- may be evaluated and transmitted by adopters and the processes by which competing artifacts may serve to form and transform groups of adopters or a client base. Such models also contribute to a formal consideration of the processes by which some artifacts may dominate and prevail throughout extended periods contributing to the understanding of artifact life-cycles as well as the co-existence of alternative and complementary artifacts. Elementary models of social influence enable close inspection into first principles of agent-group interaction, particularly related to the emergence of shared values which are of particular relevance to design studies.

It is the aim of design practitioners to innovate and bring about social change, which could be intuitively seen as a process opposite to the spread of artifacts and the emergence of clusters or converged structures. That is, if designers are interested in expanding their user base by continuously increasing the number of satisfied individuals that adopt their design artifacts, the generation of an alternative artifact could be seen as to cause the reversal of the desired effect, i.e. the dissolution of a social group. This apparent contradiction is open to study using a model of social influence adopting a theoretical view of social change [9]. In this paper we explore a simulation framework that addresses a series of elementary aspects of social influence by which a dominant artifact may be replaced by an alternative artifact illustrating the

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classic notion of *creative destruction* [10]: the recurring cycle that revolutionalizes a social structure from within, "repeatedly destroying an old one and creating a new one".

The maintenance of social diversity has been of interest in the agent simulation literature [11, 12]. However, not many models of social influence seem to explore the possible sources of such diversity and their relation to convergence. Axelrod [1] suggests that a model of social influence needs to include *social drift* proposing this for future extensions and advancing explanations for why diversity may persist. In this paper we address design activity as a key source of diversity and social change triggered by an individual [13].

Such macro-micro link of social change is arguably one of the open questions in social studies [9] and one in which agent-based simulations could extend the dominant individualistic approach to inspect circular causation [14]. It seems relevant to discern and experiment with possible processes that may initiate social change. In this paper we take Axelrod's [1] model of social influence to hypothesize what other mechanisms (if any) are necessary within the agent-group interaction in order to trigger a collective change. To address this question, extensions to the original model are explored to examine some aspects of divergence. Some limitations of cellular automata modeling are illustrated in this study and the need for an agent-based approach that introduces an appropriate level of analysis is elaborated.

2 Inspecting Convergence

Axelrod's model of social influence [1] is a variant of the voter model or the stochastic *Ising* two-dimensional model [15]. These models capture properties of ergodic systems, i.e. those with a recurrent invariant measure to which global convergence tends to occur for any initial distribution. In *d*-dimensional models where $d \geq 3$ random walks become transient and a probability 0 of total convergence is approached. Nonetheless, significant variants of these models such as where the state space is not compact are still important open questions [15]. Agent-based simulation offers a way to empirically experiment with these phenomena.

Claims related to these models tend to be overstated and validation remains arguably the most important aspect of agent-based simulation. In this paper the term 'culture' is used for explanatory purposes and defined after Axelrod [1] simply as the set of values shared by a population of individuals or sites. Dissemination of culture in a cellular automaton (CA) model of homogeneous sites in a two-dimensional space addresses how a community (i.e., a group of individuals with common values) forms according to the exchange of elements among its individual members. The model describes an individual's culture in terms of a fixed space of features or variables and for each feature a set of traits or values. Equivalent results are observed in our replication on a torus grid where sites on the edge interact with the neighboring site in the opposite edge of the grid. Site interaction consists of sites checking for a shared trait with a random adjacent neighbor and picking a different trait, if any, to copy from the neighbor. The execution of this behavior description and the interaction of these simple behaviors within a shared space produce interesting phenomena. More formally the model is described as follows:

1. Let culture *c* at a site change as
2. select a random site *s*, a random neighbour of that site *n*, and a random feature *f*
3. let $G(s, n)$ be the set of features *g* such that $c(s, g) \neq c(n, g)$
4. if $c(s, f) = c(n, f)$ and *G* is not empty, then select a random feature *g* and set $c(s, g)$ to $c(n, g)$.

The main results of this model revolve around the emergence of cultural *regions:* sets of contiguous sites with identical culture. Namely, what determines region formation or convergence in this model includes the range of cultural values, the range of interactions, and the size and configuration of the space. For instance, with the Moore neighborhood (i.e. eight adjacent neighbors) the final configuration presents fewer stable regions than with the Von Neumann neighborhood showing that increased interaction channels cause further convergence. Equally, in spaces populated by agents that can displace to other sites, the convergence rate decreases. Cultural *zones,* on the other hand, are defined in this model as sets of contiguous sites with compatible cultures where compatibility exists if at least one feature is shared. Increasing the number of sites in a population results in a lesser number of final stable regions because sites will have more time to integrate within a common zone. In other words, bordering regions that were incompatible will take longer to converge and this gives more time for a third culture to 'break the ice' and make interaction possible across otherwise incompatible boundaries. Henceforth, temporal and spatial conditions under which agents interact are seen to have an effect on group formation, even if the individual agents have constant characteristics.

As the number of traits decreases fewer regions survive since from the initial configuration most sites will share at least one value and thus there are only small chances of an individual being incompatible with the rest. From the outset the population consists of one large compatible zone. On the other hand, small feature spaces tend to hinder agent interaction since the chances of having a compatible adjacent neighbor decrease. In that case multiple alternative regions become locked-in rapidly. Again, by adjusting the amount of cultural variants, the size of the population, or the interaction channels, it is possible to manipulate the range of final stable regions. Figure 1 shows five typical cases of populations of agents having 3 to 15 features with ten traits each, where culture diversity is plotted against iteration steps. These five cases show how variance in one parameter affects the convergence trend. Notice the ergodicity of the system, i.e. the equilibrium state to which the system tends to convergence for any initial distribution.

One central issue towards the inquiry of divergence phenomena is already visible in Fig. 1 in relation to the emergence of new cultures during a system run. For instance, if agents have values with a format of five features each with ten possible traits, then two neighboring agents could have values of say 8-7-8-3-1 and 9-7-2-6-4. These agents share a trait (the second feature is 7) and are likely to interact. At the next event, the ensuing value could result in 9-7-8-3-1, thus potentially generating a new culture by a kind of crossover process. Under some circumstances, this divergence can be significant as illustrated in Fig. 1 where system runs with a larger number of features present steeper divergence stages as part of the convergent trend.

Divergence is defined by culture variety increasing over time. Figure 2 shows a more dramatic case after a Monte Carlo simulation (20 system runs) of a population of 100 individuals with 10 features and 20 possible traits.

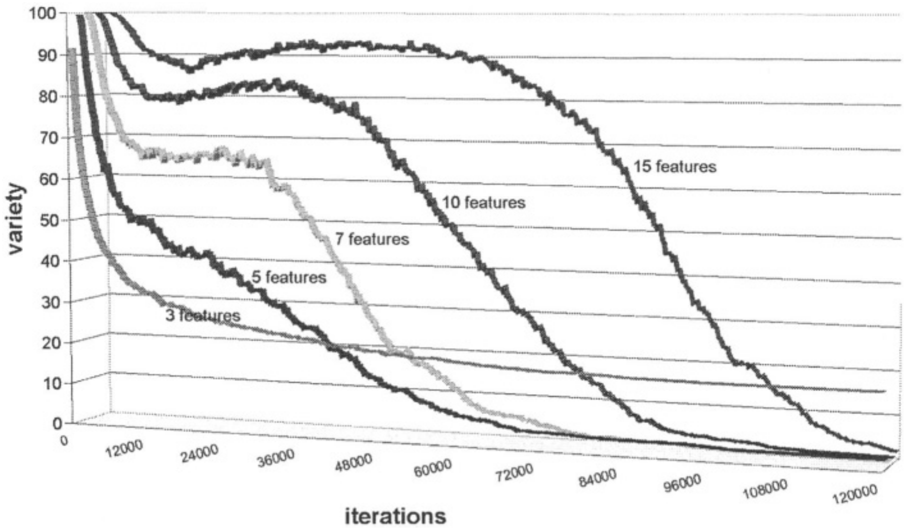


Fig. 1. Convergent trends of five typical populations with varying features (3 to 15) with ten traits each feature. As the feature space increases, divergence stages appear within the convergence trend (humps in variety over iteration steps). All cases consist of populations of 100 individuals run over 120,000 time steps.

Figure 2 illustrates an implicit and necessary divergent process within the existing convergent trend. As cultural diversity increases new value combinations appear and the less control that any single individual has over a dominant culture since agent interaction will collectively transform group culture. This is reminiscent of the fundamental principle that controlling how a set of values will be disseminated through a population is indeed difficult for any individual. Instead, once the value is released, it is subject to contingencies of social interaction [9, 18]. In design disciplines this could point towards the fact that a design artifact is commonly transformed by its adoption and use by members of a population. The designer is therefore in control of features discernible at the time of conception and much of design activity is in fact concerned with problems caused by previous design solutions.

In regards to the possible role of change agents it is noticed that intuitively, the formation of dominant zones and regions would support the observation that "a majority culture is more likely to survive than a minority culture" and similarly that "a larger region is more likely to 'eat' a smaller region that the other way around" [1]. From this observation the role of designers in generating alternative artifacts to replace a dominant one would appear in principle highly unlikely if not impossible. Notwithstanding, design practitioners are indeed deemed as able to trigger social changes [13]. It is our aim here to explore what particular mechanisms are necessary

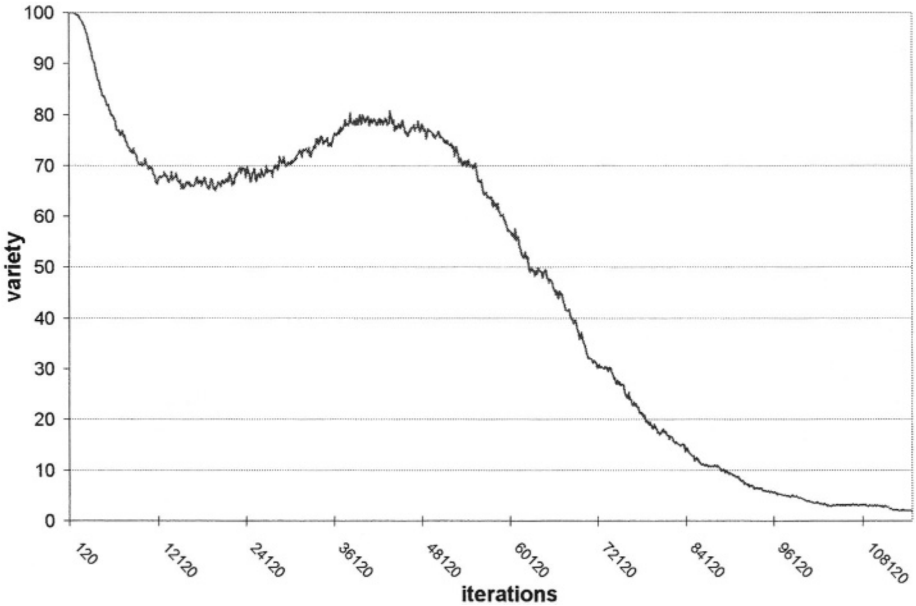


Fig. 2. Monte Carlo simulation with 20 runs of a population of 100 sites with 10 features and 20 traits over a period of 120,000 iterations. Notice the divergence stage characteristic of the general convergence trend. New cultures are created as a product of site interaction.

to enable an individual to trigger a social change. How could it be possible for a minority - of initially only one differing individual – to spread an alternative value across a social group with a dominant converged culture? Figure 3 illustrates the intuition that a majority region tends to 'eat' the smaller region [1] conveying the idea that a small group would inevitably be absorbed by a larger cultural group -or remain isolated if incompatible.

The next section presents extensions to the model where an alternative value is periodically introduced addressing the capability and conditions under which an individual may transform its social group.

3 Exploring Divergence

This extension of the model proposes that faced with perceived routineness and uniformity, an individual may dissent. The aim is to observe the conditions under which such a dissenting individual may be able to trigger a group change that has an effect on the majority of the population causing the rest of the population to adopt the alternative value. The algorithm of social influence is the same as Axelrod's [1] except for the following procedure added to the model: if all perceived adjacent neighbors have the same culture, and with a given a probability *Pn,* set a random feature to a random value, where the probability is an independent variable. More formally:

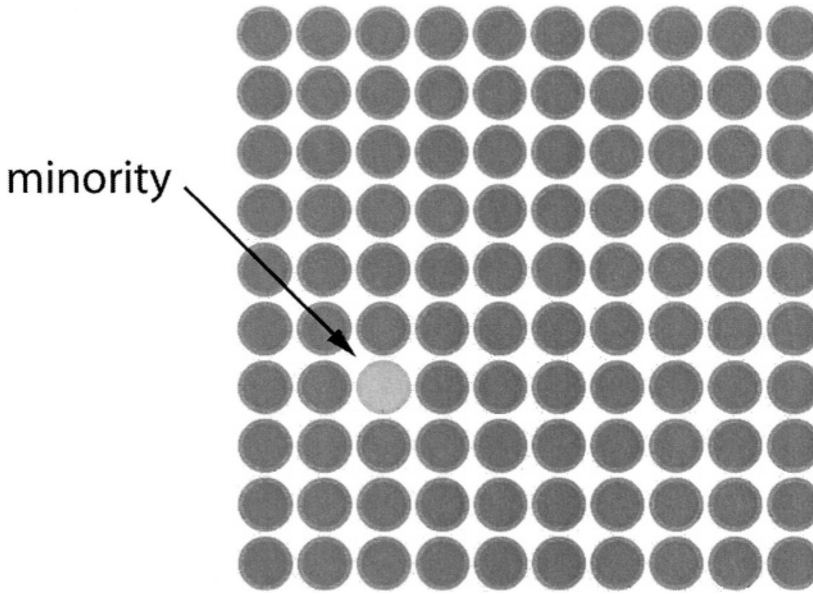
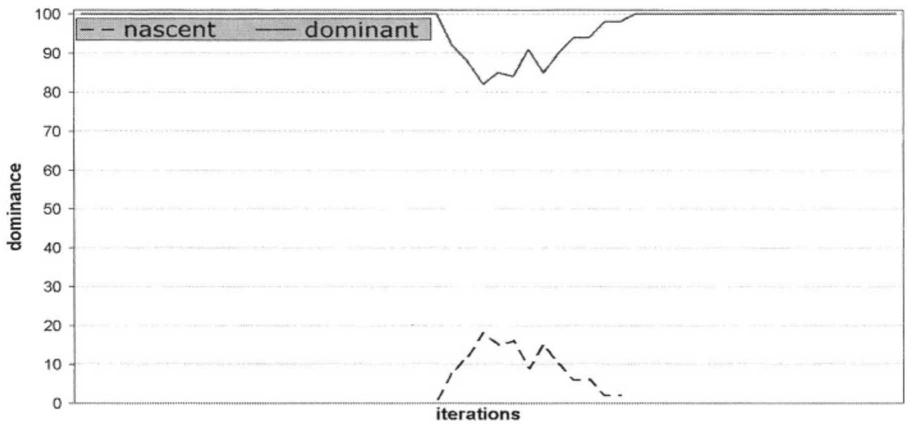


Fig. 3. Design activity is seen as a minority, of initially one individual, triggering a collective change, a notion apparently unaccounted for in a model of social influence that focuses on the formation of convergent structures. Minorities like the one shown in this figure are likely to disappear and be replaced by a dominant culture.

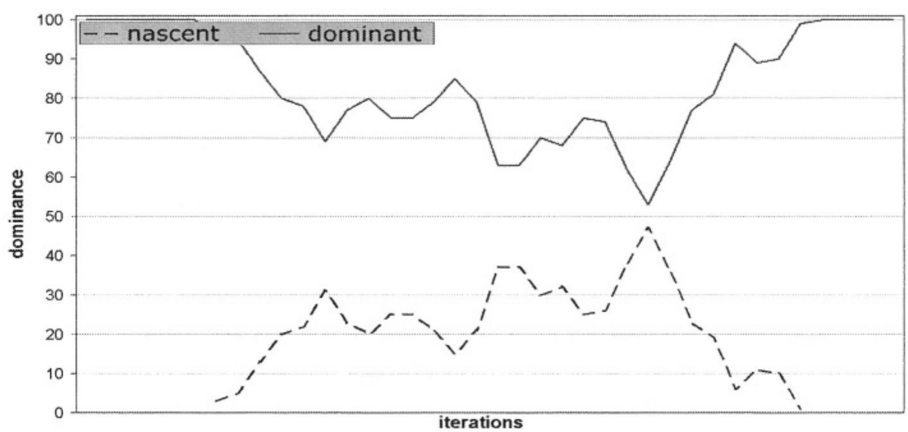
1. Let a site s introduce an alternative feature f in culture c as
2. select all adjacent neighbours $\boldsymbol{n_n}$
3. let $G(s, n_n)$ be the set of features g such that $c(s,g) = c(n_n, g)$
4. with a probability Pn, select a random feature g and set $c(s, g)$ to $c(s, \Delta g)$.

One way of estimating the ratio of change within a population from a design viewpoint is in the proportion of designers to the rest of society. Consider the recent U.S. Decennial Census of 2000 where the Standard Occupational Classification shows that 0.177% of the population of the United States works in the creative design professions (SOC codes 27-1021 to 27-1027). The extension to the model is thus set with a stochastic condition that enables a change probability Pn of 0.177%.

In a typical system run initial conditions are seen to play a minor role with this change rate since the population initially follows the convergence trend illustrated in Fig. 1. In contrast, noticeably higher change rates prevent the formation of zones and regions since values repeatedly change before they can be spread across the population. Notice the restriction by which agents aim to replace a value when they perceive that all their adjacent neighbors have the same value, i.e. local routineness. In this case we focus on the change rate specified above because it allows the whole population to form a single dominant culture where the impact of an alternative value is easier to inspect. Figure 4 shows a set of episodes in a control case where the dominant culture, i.e. adopted by all individuals in a population of one-hundred (continuous line) faces the introduction and spread of an alternative culture (dotted line) with varying outcomes.

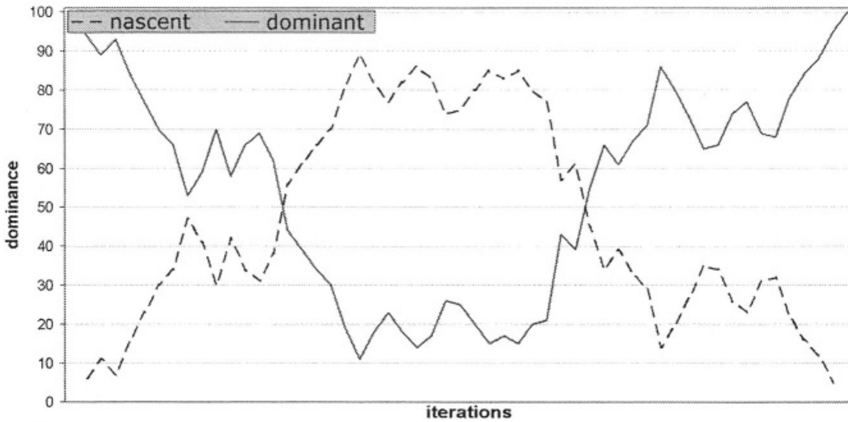


a)

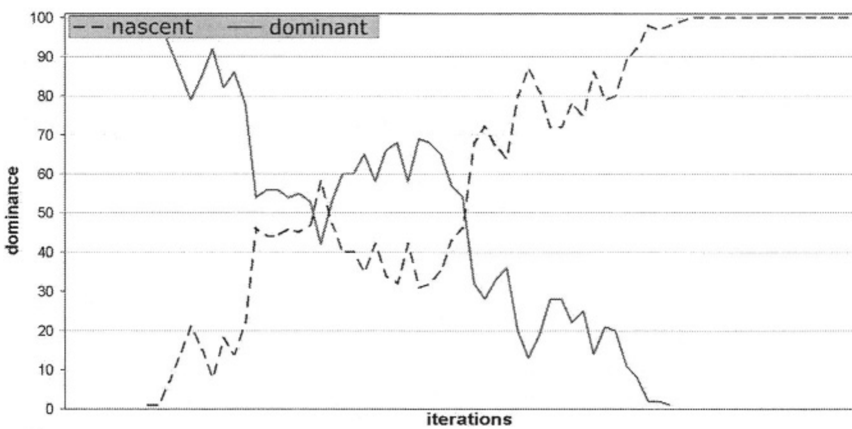


b)

Fig. 4. Episodes where a dominant culture (continuous line) is challenged by the emergence of an alternative culture (dotted line) with varying consequences. Case a) shows a nascent value that is spread to a maximum of 18 individuals before it decreases and disappears. A mirror effect in the dominant culture is seen as individuals exchange adopted values. Case b) is an episode where the competing cultures reach around fifty percent of the population, after which the dominant culture returns to total dominance. Case c) shows the dominant culture decreasing until only eleven sites share the value only to come back to dominance after a number of time steps. Lastly, in case d) the dominant culture is replaced by an alternative value that is spread across the population.



c)



d)

Fig. 4. (continued)

After the population converges in a stable region of total dominance, change episodes occur periodically over extended periods. This is at first counter-intuitive since dominant cultures were assumed to 'inevitably' take over marginal compatible cultures. In fact, such explanation appeared obvious before this extension when it was concluded that longer interaction times facilitate the dominance of a single culture. In some of the cases shown in Fig. 4 the prevailing culture (shown with a continuous line) reverts to dominance and in others it is replaced by the alternative value (shown with a dotted line). In Fig. 4, case a) shows a nascent value that is spread to a maximum of 18 individuals before it decreases and disappears. A mirror effect in the dominant culture is seen as individuals exchange adopted values. Case b) is an episode where the competing cultures reach around fifty percent of the population, after which the dominant culture returns to total dominance. Case c) shows the dominant culture decreasing until only eleven sites share the value only to come back to dominance after a number of time steps. Lastly, in case d) the dominant culture is replaced by an alternative value that is spread across the population.

At first, it appears counter-intuitive that the same mechanism that enables a social group to reach consensus and form a cohesive collective unit would support dissolution of the group and reformation around a new value. However, it is precisely the tendency to stabilize a shared culture that occasionally facilitates the spread of an alternative value even when this is initially assumed only by one single individual. In this way group divergence may actually consist of a kind-of-convergence that produces collective change. During these system runs a number of alternative values are introduced but most attempts to overtake a dominant culture are unsuccessful, i.e. the case of Fig. 4a occurs more often than others.

Models of social learning [16] suggest that imitation benefits a population only when coupled with some amount of individual change. Divergence or innovation may thus not be regarded as an extraordinary, opposite, or separate factor of social convergence or imitation [17]. Instead, it appears as an essential component inherent to the system in a fundamental way [10]. However, most research on the diffusion of innovations is characterized by the pro-innovation bias [18]: the assumption that a new solution ought to be spread and adopted by some or all members of a social system. This bias restricts inquiry to after-the-fact phenomena, impedes access to the study of unsuccessful solutions, and limits access to rejection mechanisms, discontinuance, and re-invention that may occur during evaluation and diffusion stages. This suggests that despite being numerous and potentially illustrative, cases like the first three in Fig. 4 have largely remained outside the literature reporting on such studies. In all, this model captures an elementary notion of co-dependence between convergent and divergent structures. Perhaps the strength of this model is that it shows in a very simple way that individuals need not invoke any extraordinary mechanism to transform their social group [9]. The same basic mechanism of social influence that initiates a social group appears sufficient to produce the recurrent occurrence of social change.

Moreover, it has been argued that the formation of shared values generates a notion of *normality* [19] that facilitates collective work, communication, and judgment. Individuals may not be able to lean on culture if a higher rate of change is introduced in a population, i.e. everyone would need to learn independently and no collective structures of support would emerge. Clearly, further experimentation is needed to understand the conditions under which social influence may in fact generate group change.

One more aspect that can be inspected in this model deals with the interaction between more than two competing cultures. This is an interesting process but one that soon becomes hard to keep track of. Consider for instance Fig. 5 where a cycle of group changes is shown in a control case.

In Fig. 5 it is possible to observe cycles where a dominant culture is challenged by the appearance of alternative values, which often disappear after being shared only by a minority of individuals (solid lines at bottom of graph). This is reminiscent of the ratio of successful innovations [18]. In this control case five different cultures become dominant during varying time lengths whilst around one hundred alternative values were introduced. The total system run consists of a population of 100 sites with initial conditions of total convergence and the data is recorded during 250,000 time steps.

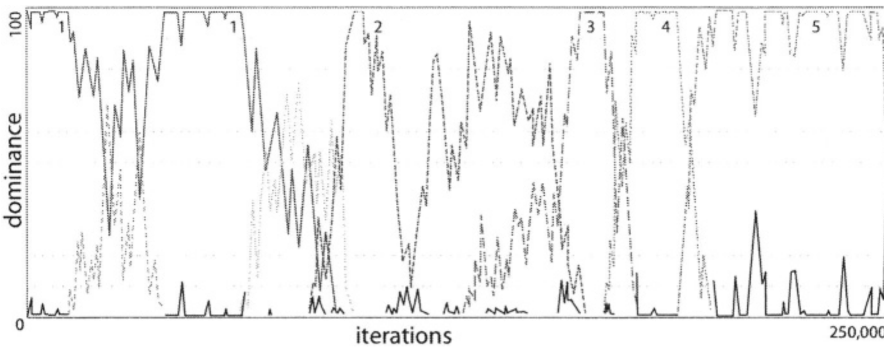


Fig. 5. A typical system run of a population of 100 sites with alternative values introduced with a 0.17% probability. Cycles of convergence and recurring culture replacement occur. In this case five dominant values appear at different times throughout 250,000 iteration steps. Dominance is defined by the adoption of the value by the total number of individuals. In cases 1 and 5 the dominant culture regains dominance a number of times. In contrast unsuccessful values often disappear before being spread beyond a minority (lines at the bottom of graph).

Figure 6 illustrates the interaction between competing cultures in the period between time steps 75,000 to 107,500 of the control case shown in Fig. 5. In this episode a dominant culture is seen to decrease (line A) as a competing value is spread (line B). Around time step 95,000 a third value is introduced by a different site (line C) and in the boundary between the two alternative values a fourth *new* value appears and gains dominance (line D).

What is interesting in this control case is that the fourth value (line D) is not strictly 'new' but is a consequence of social influence: a combination of traits introduced by the two alternative values (lines B and C). In other words, the 'novelty' of the fourth value (line D) is not introduced by the specified behavior but is an emergent result from combining traits through the normal dissemination mechanism. Later, this mediated value becomes dominant. The reason may not be immediately apparent. Arguably, the fourth value (line D) becomes dominant because it capitalizes on the spread of the other values and since the original mechanism of social influence supports the dissemination of different traits (i.e. check for shared trait, copy different trait) the new value reconciles competing alternatives and benefits from their diffusion. This can be called *opportunistic innovation* and may be a significant component in the diffusion of innovations, in particular concerning the unexpected consequences of innovations [18].

4 Discussion

Social processes of convergence and divergence may be intuitively attributed to separate and somewhat opposite mechanisms of interaction. In this paper we have approached agent-based simulation as a viable way of experimenting with and thinking about such interaction mechanisms. The results of this experimentation point

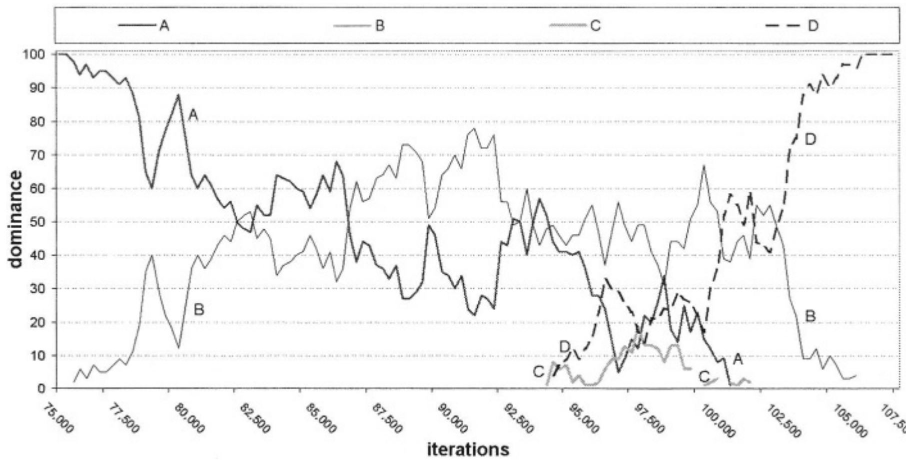


Fig. 6. A change episode is shown here where a dominant culture is challenged by two alternative values, after which a fourth new value, generated by the dissemination mechanisms, becomes dominant.

towards a complementary role between convergence and divergence processes in the generation and diffusion of innovations. Such experiments are significant in that they allow the exploration of an interdependency which may be intuitively difficult to recognize [1]. Whilst mere group convergence may generate value diversity (see Fig. 2), extensions to this model further show that the response of one differing individual to perceived routineness may be sufficient to trigger collective change through the same convergent mechanism that brings about group coherence if and only if appropriate conditions exist for the generation and impact of such action. Therefore, the formation and transformation of adopter communities may occur through a common process of social influence where the *status quo* is disturbed by the appearance of an alternative minority value around which the social group reassembles.

Findings from these simulations do not have a direct mapping into human social phenomena. Value exchange as a model of culture is not based on an assumption of resemblance but on one of reflection. Namely, this model illustrates that when culture and social interaction consist of a fixed space of features being directly transmitted by homogeneous neighbors, complementarity and not contradiction exist between convergence and divergence. Further, under such conditions individual differences are regarded as insufficient to explain change agency since all agents' actions being equal, only those that are located within certain external conditions may become influential. Perhaps the most significant aspect about this model of social influence related to an inquiry of design and innovation is in its capacity to capture at an abstract level an incipient relation of change phenomena to individual and situational conditions.

Design studies characterize designers as change agents of their society [13, 20]. The results presented here suggest that - in principle - it is indeed possible for an individual to trigger a social change and that in order to do this it is not necessary to invoke any special mechanism other than that used to account for group convergence and occasional individual disagreement. Although this is a simplified view of the dynamics involved in social change - particularly the agent/structure relation - it points to the following insights in relation to innovation and creativity in design.

Firstly, the eventual success of an individual that aims to change their society has been separated in this model from any explicit notion of *utility* suggesting that the merit of widely-spread values across a social group need not be related to the particular attributes of that value. In design disciplines this may have important implications, including the partition between quality and creativity. Whilst it is possible to describe and measure the former within the internal characteristics of a design artifact, explanations of the latter need to include the relation of the artifact to the socio-environmental conditions within which it operates. Thus, the creativity of an artifact is not a stable endogenous property but a temporal ascription that takes place in its interaction with other agency entities both at the individual and collective levels. This is an important departure from the notion of an individual and only an individual being creative.

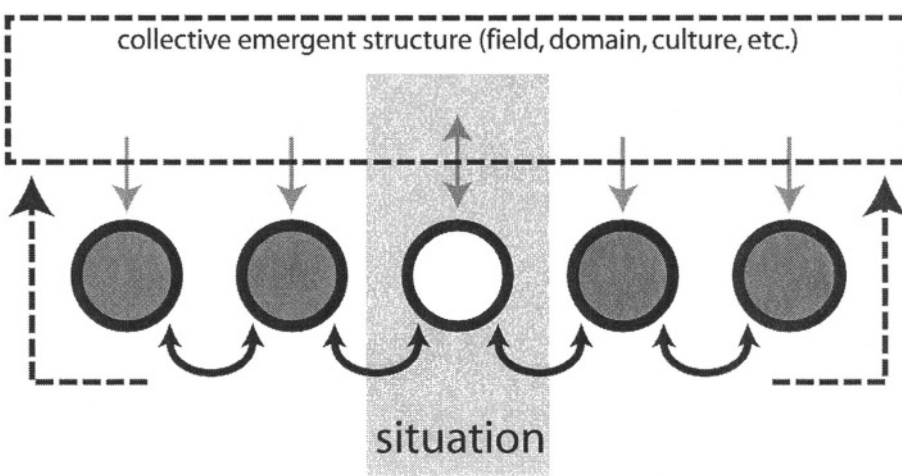


Fig. 7. A situation-based approach to extend the cellular automata CA model presented in this paper. The aggregation of agent interaction generates emergent collective structures that feedback the members of a group. An agent may be located within a relevant situation in which individual characteristics and situational factors support influential behavior.

Secondly, the observed change cycles suggest that successful innovations (i.e. widely spread) may only take place sporadically irrespective of the number of attempts. If a population is to follow a convergence trend to give rise to cohesive groups then there would be a collective limit to the frequency of possible innovations. Inquiry into the factors that may determine the innovation rate of a social group is largely an open question in design and social science.

Thirdly, the results presented here similarly suggest that at the individual level designers and other creative practitioners may be restricted by a social ceiling of influence. That is, in order to become influential, a creative designer would depend upon a collective process by which others are indeed influenced. Persistence or persuasion may thus be a more important personality trait to creativity than 'imaginative thinking'. The implication that influential people or ideas are not necessarily the best but could have been in the right place at the right time [22] challenges the mainstream view of creativity. To any extent, socially-ascribed 'creative people' do shape their societies but are also product of social dynamics themselves and in the end whom we end up regarding as creative may not necessarily be more imaginative, ingenious, or inspired than the rest of us.

Nonetheless, the advantage of simplification in cellular automata (CA) modeling carries non-trivial limitations. In experimenting with convergent and divergent mechanisms, this framework has alluded to the fundamental relation between agent and social structure. It is within this interaction where a) influential agents gain such role and b) adequate social conditions arise. However, these interactions are largely concealed in the CA approach and it seems necessary to modify the modeling assumptions in order to make this interaction explicit [20]. Namely, whilst these simulations make clear that the individualistic stance that dominates creativity research may be insufficient to define a change agent, the external variables that define a situation of potential change are hard to pin down. A possible solution to this shortcoming could be in the extension of the CA paradigm to include an intermediate level of analysis between agent and group structure. A *situation* could be an appropriate modeling tool when defined as the construed relationship of the agent's internal state and perceived external conditions. In this way, an agent's situation could be inspected and its role in determining change agency asserted. Figure 7 shows the idea of a causation model in which an agent interacts with other agents (social competence), out of which a group structure emerges (culture, domain, field) that in turn feedback to the individuals. An influential situation may be recognized as the space within which the generation and impact of influential behavior is made possible (i.e. window of opportunity). A situation of this type coupled with relevant individual characteristics would support the occurrence of an outcome that modifies the existing group structure when adopted by others. The focus on the relevance of agent and situation points towards their co-causation, i.e. individual differences caused by situational differences and vice-versa.

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Social Prejudice: Cognitive Modelling and Simulation Findings

Livio Noto[1] , Mario Paolucci[2], and Rosaria Conte[1,2]

[1]University of Siena, Italy;
[2]ISTC/CNR, Rome, Italy
{paolucci, conte}@ip.rm.cnr.it.
http://wwwistc.ip.rm.cnr.it/lss/

Abstract. In this paper, after discussing very shortly the relevant literature on prejudice, we propose a simulative model to contribute answering open questions in the field. The model builds upon previous work on social artifacts, especially reputation. A set of simulations is run in different conditions; effects of book keeping, of communication and of reputation/knowledge heredity are presented, under various mutation rates and noise levels. The paper concludes that, in the simulated conditions, prejudice extends the positive effects of reputation if the error is low enough. Prejudice can be seen as a mechanism for generating knowledge from simple assumptions, but becomes useless as error rates grow, possible due to anonymity and/or larger populations.

1 On Prejudice: Classic Approaches and Open Questions

Social prejudice has been defined [2] as a cognitive "error" (false generalisation) directed towards a whole group or one of its members simply because of his or her affiliation (see also [14]). According to [4] (as well as [1, 12, 13]), prejudice is a large label subsuming sexism, racism, homophobia etc., concerning not only cognitive, but also emotional and behavioural, attitudes, i.e. stable tendencies to respond favourably or unfavourably to particular stimuli. Emphasis has often been laid on the static nature of prejudice, refractory to falsification (see [7]). However, in a number of experiments (cf. [4]), prejudice is found to change over time (think of the expression "modern racism"[1] and of the subtle forms of prejudice currently spreading [10]). Furthermore, prejudice is not necessarily negative: it can also be positive, although with a lower frequency.

There are three main approaches to prejudice: social categorising, conflict of interests, and social identity. None of them (for a review, see [9]) provides general and satisfactory answers to the following questions:

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[1] Pettigrew and Maartens [10] distinguish between hidden, or current, and open, or traditional, racism ([3] speak about modern *sexism*). Taking into account both the traditional and current typology, [8] documented that no correlation exists between either and personal interests. Apparently, in modern prejudice an increased difference is perceived between in-groups and out-groups [11].

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- Why, what are the effects and functions of prejudice? Is this a mere pathology, an undesirable social effect of individual motivations (as is implied by the theory of social identity), or, instead does it have specific social functions, which also allow and account for its undesirable effects?
- What are the connections between prejudice, on one hand, and more general social evaluation, on the other?

What is needed is (a) an explicit theory of prejudice and evaluation in their cognitive and social aspects. (b) A theory of their connections, enabling to formulate hypotheses as regards their social effects or possible functions. (c) A solid experimental methodology allowing large-scale experiments to be carried out in order to verify such hypotheses.

Here is where agent-based computer simulation of social phenomena can help. For both ethical and technical reasons, it is extremely difficult to carry on experiments with natural subjects on the global effects of prejudice. It is necessary to transfer the cognitive model into an agent-based simulation model, to implement it on a multi-agent platform, and to recursively refine the model on the grounds of the experimental findings. What we present here is a set of results from a simulation experiment based on the above questions, in the hope that it can provide a basis for bettering our understanding of and our insight on prejudice.

2 Previous Work

In previous work [6], we distinguished two notions of social evaluation, *image* and *reputation.*

2.1 Social Cognitive Notions

We defined *image* as an evaluative social belief. It tells that an agent, the target, is “good” when he displays a given behaviour, and that he is “bad” in the opposite case. Image includes three sets of agents: the set of agents who share the evaluation; the set of evaluation targets; the set of beneficiaries, i.e., the agents sharing the goal with regard to which the targets are evaluated. In particular, more or less explicitly, image concerns the targets’ willingness to achieve a shared goal or interest of the group.

Reputation is instead a meta-belief, i.e. a belief about others’ minds, more specifically about others’ evaluations of a target. This bears several important consequences. First, to accept a meta-belief does not imply to accept the contained belief. Consequently, to assume that a target t is assigned a given reputation implies to assume that t is believed to be “good” or “bad”, but it does not imply to share either evaluation. Four reputation characters have been identified, Evaluator, Beneficiary, Target, and Gossiper. The first three are involved in both phenomena, whilst the last one (Gossiper) occurs in reputation transmission. Agents may spread both a true and a false reputation, i.e. pretend that others have a given image of a target, whilst this is not the case. This may be done in order to achieve a good reputation (as one that shares the group's interests) without taking responsibility for spreading a given social evaluation.

What are the collective and individual roles of reputation? Why do people contribute to its spreading?

2.2 The Simulation Model: SimNorm

SimNorm was developed in order to answer the preceding questions in the context of norm-abiding behaviour (for a detailed description of algorithms and numerical parameters refer to [5], available online; cfr. also [6]). To do so, the role of reputation was investigated in a population of artificial agents competing for scarce resources in a 2-dimensional world, and applying different *strategies* of aggression control. Each agent applies one definite strategy to decide what action to perform. One of these strategies was interpreted as a norm (not immediately useful to its performer), namely "Don't attack agents consuming their own resources (eating their own food)". The other strategies were called respectively utiliarian or "cheat" (do not attack weaker eaters) and blind (do not attack if you have an alternative way to find food).

Findings showed that the utility of the normative strategy is conditioned to the conjunction of three further mechanisms: (a) reputation of agents is stored by norm-abiders, (b) is circulated among themselves, and (c) norm-abiders retaliate against transgressors by behaving as transgressors with them. In all other conditions, norm-abiders were found to be worse-off than norm-transgressors.

On the grounds of this work, we formulated a theory of reputation as a mechanism for redistributing the costs of norm-obedience. More generally as a mechanism of social control that promotes cooperation.

3 The Present Study: From Reputation to Prejudice

In the previous study, we mainly dealt with the *transmission* among gossipers of reputation information. What about the *contagion* of reputation, from one target to another? This process may occur both horizontally (from a target to its neighbours) and vertically. In our view, prejudice is a special case of reputation contagion, which implies supra-individual entities (for example, a lineage or a group). More explicitly, *prejudice is reputation inherited by individuals owing to their belonging to a reputed lineage or group.*

Prejudice is an effect of humans' cultural evolution. What are its effects? Does it also contribute to social control and the promotion of cooperation? This is what we have investigated in a more recent study (for a thorough description, see [9]). We hypothesised that prejudice is a proxy of communication of social knowledge. As in the case of communication of reputation, prejudice was expected to *allow cheaters to be preceded by their reputation, thereby sparing the "good guys" the costs of meeting with them.*

Therefore, prejudice shares with reputation the redistribution of the costs of social cooperation. Unlike reputation, however, social prejudice starts from previous knowledge, stored after direct or indirect experience. What's the use of it, since what makes social life harsh is the acquiring of social knowledge?

The work that will be presented was aimed to test *in silico* the previous hypothesis and to contribute to answering this question.

3.1 The Simulation Model: GrRepP_Sim

The present model builds on SimNorm by taking into account not only reputation but also the strategy of attack. Unlike SimNorm, based on a presumption of innocence, GrRepP_Sim is based upon a pre-existing belief about the strategy played by agents as an effect of their lineage. Moreover, each agent is endowed with a "Book of Knowledge" (called *BoK* in the following), in which information on others' strategies (reputation) is stored. The BoK is updated by direct expertience, and by one of the following social constructs when they are active:

- Heredity of
  - reputation
  - knowledge (BoK)
- Communication

each of these can be turned on of off, in four possible combinations or sub-experiments. The no-Heredities and no-Communication combination has been considered as a control condition.

Heredity is a sort of prejudice on future actions of the reputed agent. If reputation in inherited by the offspring independent of their real strategy, we face a condition of "lineage reputation" (which becomes group reputation as long as heredity is not seen as transmission of genetic but cultural characteristics shared within a group of non-kin).

Heredity of knowledge, the transmission of knowledge from parent to sibling, is realised by copying the BoK (i.e., an array with information on other agents), allowing new agents to start with all the parent's accumulated knowledge.

A mutation algorithm has been implemented, allowing offspring to deviate from parents' strategies: we will then have normative offspring of cheating parents, as well as cheating offspring of normative parents.

Communication consists in exchange of information contained in the BoK. Two agents reciprocally update their knowledge when they meet in the two-dimensional world. Each agent accept information from well-reputed sources only. In the model, communication is expected to:

- highlight the mechanism of knowledge propagation, and to check its speed at a given density and size of the population,
- allow for the extreme condition in which knowledge is obtained only *via* direct experience.

4 The Simulation

The simulation provides (via REPAST services) both a numeric output and a visual output showing the agents' interactions on the grid, as well as figures showing the trend of the population growth and reproduction under the different experimental conditions.

A battery of experiments has been performed, by varying the following set of parameters:

- Mutation_Rate, the percentage of offspring with a different strategy from their parents'
- Communication
- Rep_Inheritance, heredity of father's reputation
- Know_Inheritance, heredity of BoK.

Agents are modelled so as to be able to adapt their behaviours to other agents and to learn from their actions (via the accumulation of information in the BoK).

4.1 Expected Results

Heredity of reputation was expected to favour good guys over cheaters because it makes a normative agent's answer faster and more efficient. This is true especially when reputation is utterly accurate.

In turn, communication was expected to yield better results than no communication. It speeds up the transmission of social knowledge within the same generation, and provides reasons for adopting a given attitude and the corresponding behaviour.

Since reproduction is a function of agents' wealth, findings are measured in terms of sub-population's reproductive fitness, expressed from the total number of agents per strategy *(population)* and the total number of *siblings* produced.

4.2 Control Experiment

In the no communication and no heredity condition, when the mutation rate is set to 5% (what is a high value from a genetic point of view, but very low from the point of view of cultural change), a clear prevalence of cheaters is obtained (see fig. 1). This is so because retaliation against cheaters is effectuated by normative agents only after direct experience. In this context, the costs of aggression control are sustained only by the good guys. Furthermore, children learn nothing from parents and are obliged to make experience at their own expenses.

In this condition, cheaters evolve more than normative agents. There is poor utility in respecting the norm, because the costs are not redistributed over the population. The normative population growths less, whereas cheaters show a stronger trend of growth. Norm obedience does not lead to extinction of the good guys, but it heavily discriminates against them.

4.3 Communication

As expected, communication plays a relevant role, allowing social knowledge to be circulated. However, in figure 2 one can see that communication works when it is associated to heredity, otherwise results are equivalent to those obtained in the control experiment.

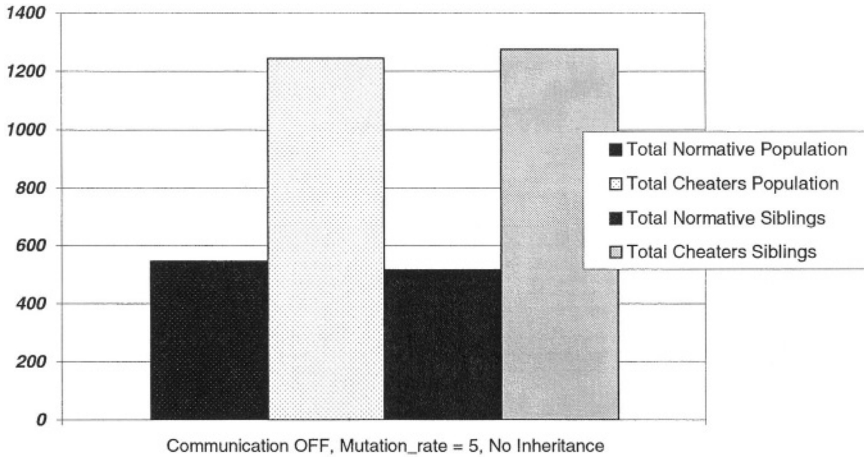

Fig. 1. Control experiment

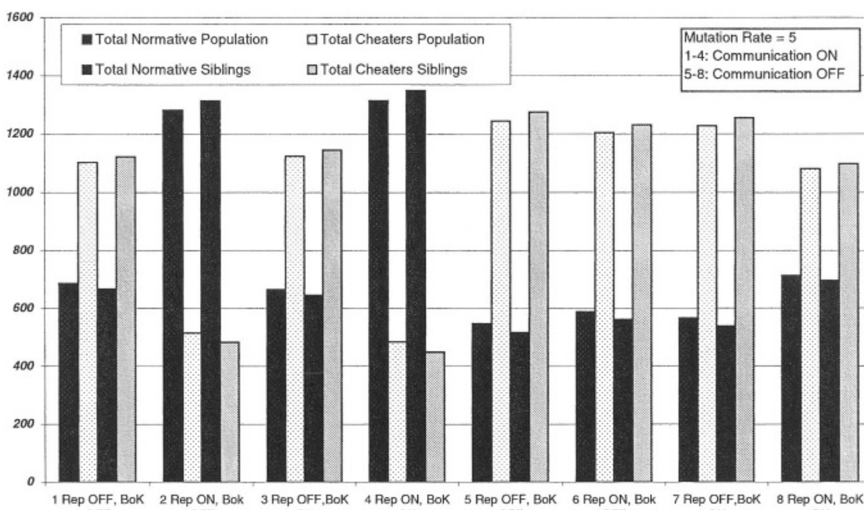

Fig. 2. Communication effect

Communication improves the results obtained by the good guys even when heredity is not active, at the same time worsening those of the cheaters. However, the normative population is still numerically lower since the information acquired by the single agent does not help much when unknown agents are met.

Transmission of social information works to the extent that it extends to the whole population. But as soon as this information is out of date (due to agents' death and birth) it becomes useless. In GrRepP_Sim communication becomes useless after a few cycles.

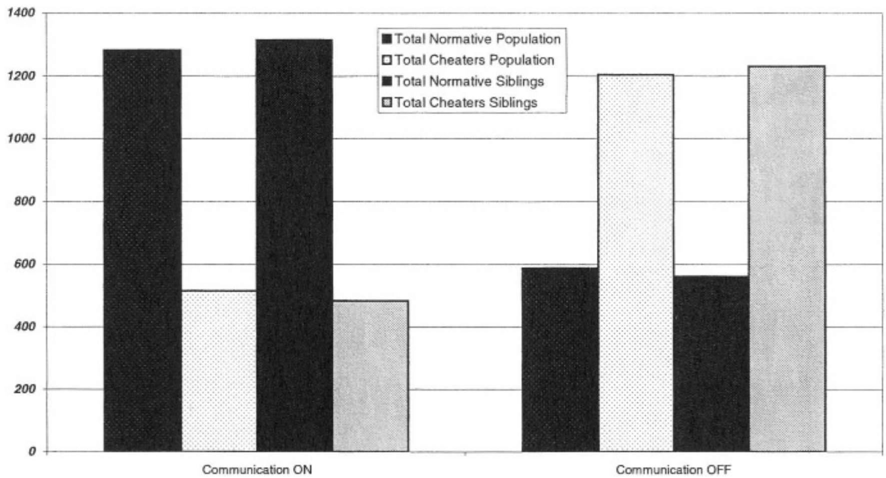

Fig. 3. Heredity of reputation

4.4 Heredity of Reputation

Comparing the size and reproduction rates of the two populations, we obtain (fig. 3) some interesting results:

- The combination of both heredity of reputation and communication yields results complementary to those obtained in the control experiment
- Both heredity of reputation and communication are influential factors (the latter more than the former)
- But neither is sufficient: heredity alone has always a poor effect, and communication alone is useless as the population evolves.

As population changes, only the combined effect of communication and heredity allows the normative agents to be effectively competitive with cheaters and to even reproduce themselves to a higher rate.

4.5 Heredity of Knowledge

When Heredity of knowledge is active but heredity of reputation is not, things get better for the good guys (+21%) and worst for the bad guys (-9.6%) *only when communication is also active.* When communication is inactive, heredity of BoK does not do any substantial good to the good guys (normative agents + 3,5%, cheaters – 1,3%).

This leads us to draw another conclusion: inter-generation transmission of information improves the outcomes of the normative agents but does not ensure them with a competitive reproduction rate.

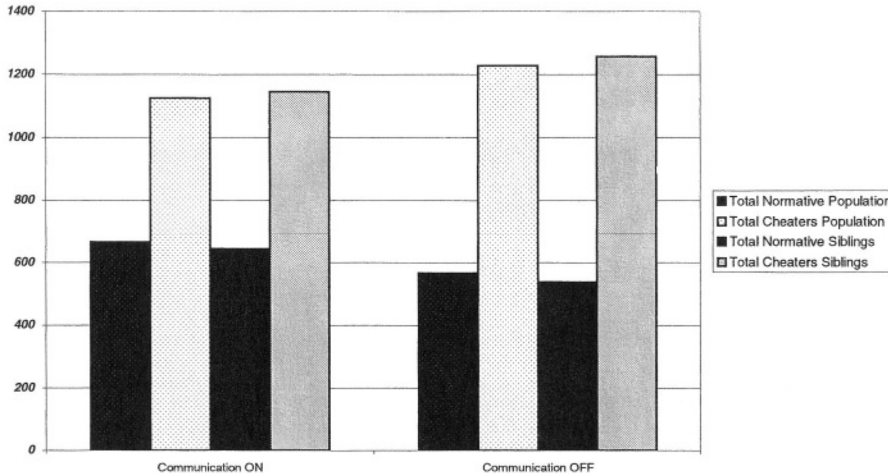

Fig. 4. Heredity of Knowledge

4.6 Combined Heredity

Figure 6 shows the results of both types of heredity with and without communication. When the latter is active, we obtain the best results for the good guys (+140%) and the worst for cheaters (-61%).

When communication is inactive improvement of the normative population is not so strong in relative terms, and cheaters maintain their dominant position (+30% for the normative agents and - 13% for cheaters).

When compared with the control experiment, the combined effect of both types of heredity plus communication leads to a clear inversion of trend: the good guys are better-off than the cheaters and reproduce more.

The reason is quite simple: thanks to inheritance, agents have a history of other agents. The probability of being defeated is an inverse function of the available information. The presumption of innocence turns into a presumption of guilt, with only a 5% error -- what gives the system efficiency and stability.

In such a context, group reputation represents an invaluable mechanism, efficient and useful, of aggression control and of costs' redistribution.

The next question is what happens if the mutation rate, and consequently the error, increases?

4.7 Error in Reputation

What is the effect of a mutation rate higher than 5%, rendering inherited reputation less and less probable to be accurate? Here, we only show the effect of error with inheritance, assuming that the necessity of communication has already been widely documented.

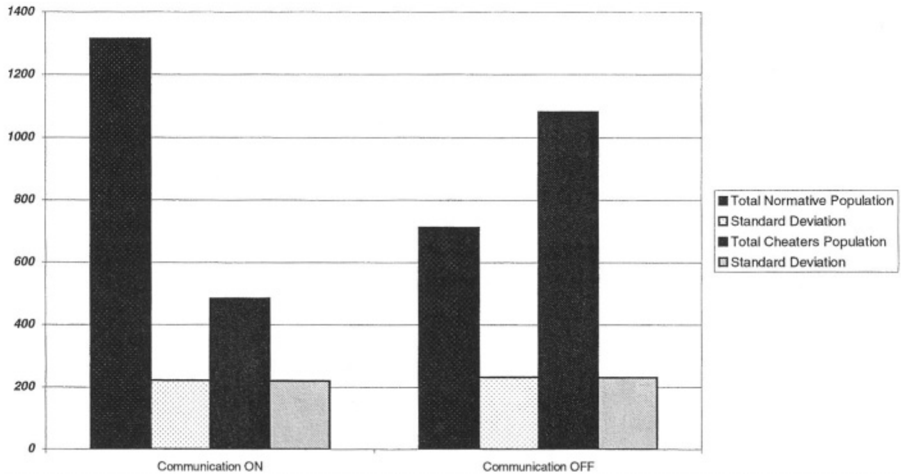

Fig. 5. Heredity of BoK and of reputation

With a mutation rate set to 50% and 95%, the values of the two populations and the number of births is essentially stable. With a growing mutation rate, effects shown so far tend to vanish.

With high mutation rates (between 50 and 95%), two main effects are obtained:

- Error, negative when a good guy is ill-reputed due to its lineage and positive in the opposite case, nullifies the effects of reputation; consequently
- The advantages of heredity of reputation decrease as error increases.

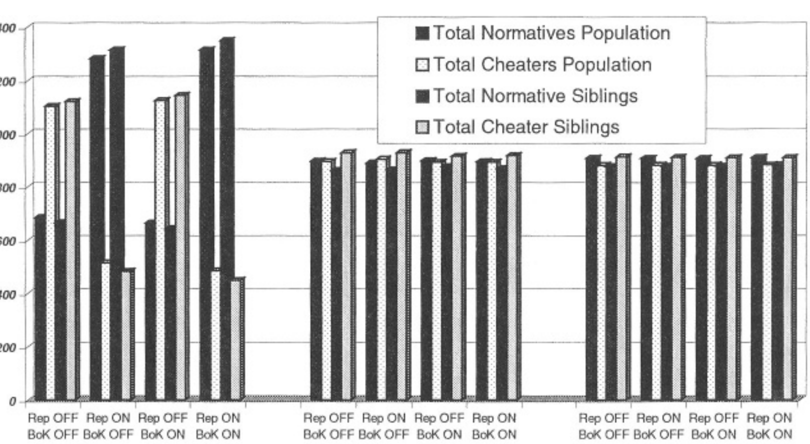

Fig. 6. Mutation rate

As regards the dependence of cheaters/normative ratio from the mutation ratio, we run a check with different levels of mutation, from 5% to 95%. The results expectably show that the higher the mutation rate, the more the agents tend to act as cheaters, since mutation falsifies the premises for the useful application of knowledge. In other words, with a large probability of error, prejudice (inheritance of reputation and of BoK) hinders the redistribution of norm obedience costs.

5 Discussion

Which conclusion can we draw from the findings presented so far?

Reputation was found to allow for a redistribution of the costs of compliance with some norm of common utility in populations of artificial agents competing for scarce resources.

When prejudice is seen as an extension of this mechanism, and therefore implemented as inherited reputation, the same effect is obtained to the extent that the probability of error, i.e. the difference between the strategy actually played by agents and their reputation, is moderate (below 50%). When error is low enough (around 5%), prejudice, or inherited reputation, has positive effects on the efficency of the norm:

- It allows for *social knowledge to be available even in open highly dynamic societies* (whereas individual reputation and its communication works only in stable societies with low mortality)
- On its grounds, a behavioural attitude is constructed (i.e. prevent aggression, avoid presumed cheaters, or retaliate against them) at the expense of ill-reputed agents.

These findings suggest that prejudice may be studied as a mechanism for generating knowledge starting form existing one. To a large extent, its utility is conditioned to the probability of error occurring during the process of generation, what equals to saying that prejudice may evolve in low-error phases, but may become useless as error grows in knowledge generation, which can be due to many factors, including larger populations and growing isolation and anonimity.

With course-grained rules (for example, simple inheritance) for knowledge generation, the probability of error is necessarily large. With finer-grained rules, accepting inherited reputation of agents as candidate knowledge -- to be monitored and possibly revised in presence of counter evidence, error can be controlled and its negative effects reduced or compensated.

In future works, rules for monitoring social knowledge should be modelled and their effects in should be observed by means of simulation.

Furthermore, a qualitative analysis of the effects of positive errors Vs negative ones should be done. Evidence from our previous simulations shows no symmetry in false reputation [6]: calumny is less detrimental than optimism to norm-abiding agents. Are these results confirmed in the case of prejudice?

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A Methodology for Eliciting and Modelling Stakeholders' Representations with Agent Based Modelling

Nicolas Becu[1,2], François Bousquet[1,3], Olivier Barreteau[2], Pascal Perez[1,4], and Andrew Walker[4]

[1]CIRAD, Montpellier, France
francois.bousquet@cirad.fr
[2]Cemagref, Montpellier, France
{nicolas.becu , olivier.barreteau}@montpellier.cemagref.fr
[3]IRRI, Bangkok, Thailand
[4]Research School of Pacific and Asian Studies, The Australian National University, Canberra, Australia
{pascal.perez , andrew.walker}@anu.edu.au

Abstract. In the frame of using models to promote dialogue among stakeholders, we are interested in modelling representations as a mean to share viewpoints and opinions. A first trend for modelling representations uses socio-cognitive theories as frameworks for modelling. This article proposes a different approach combining Knowledge Engineering elicitation techniques and Agent Based Modelling. The use of elicitation techniques provides a methodological framework to capture representations directly from stakeholders' discourse. Agent Based Modelling serves as a modelling structure which enables managing representations' heterogeneity and conflicting opinions. The proposed methodology is detailed and applied to farmers' representations of runoff and erosion in south of France. To achieve the construction of a running model of the interviewees' shared representation, it was necessary to implement theoretical data supplementing the elicited information. We argue that companion modelling approach can help sharing and discussing those non-elicited information with stakeholders.

1 Introduction

Since the beginning of Mabs workshops a group of researchers have been working in the context of natural resources management and ecosystem modelling with Multi-Agent Based Simulation (MABS) [1,2,3]. The focus is on the interactions between bio-physical and social dynamics as a mean to understand the emergent behaviours of a system. At Mabs 2000, [4] clearly demonstrated the importance of the heterogeneity of agent's representations. Thus, since that time emphasis has been put by our group on the modelling of representations, and more precisely on the modelling of stakeholders ones from the observation of the reality. The assumption is that MABS models can be used to model the various representations and decision-making process as it has been proven highly useful in simulating agents with different viewpoints and behaviours [5]. As stated by Drogoul [6] in his invited paper at Mabs 2002, the definition of the behaviours of the agents is often not a formal procedure. Thus the

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question is on the methodology to be used for the elicitation of stakeholders' representations and their modelling.

The scope of this paper is to present how representations may be modelled and to propose a methodology dedicated to stakeholders' representations modelling using elicitation technique. This modelling of representations is taking place in the overall context of producing models to facilitate dialogue among stakeholders. In this context the assumption tested in this work is that models designed upon "indigenous" representations allow sharing representations among stakeholders when used as simulation tools. This led us to the question of the methodology to go from such representations to a formalized model tackled in this paper.

In the first chapter we will look at models of stakeholders' representation using Multi-Agent Systems (MAS) as well as the use of elicitation techniques used in Knowledge Engineering. In the second chapter we describe the fundamentals of our methodology, which uses elicitations techniques. Then we present an application of this methodology for water management issues in an agricultural catchment in Southern France. This leads us to questions, addressed to the field of computer science about the use of elicitation techniques for modelling representations.

2 Modelling Representations with MAS

In order to model heterogeneous opinions with MAS, each agent is defined with specific abilities, goals and strategies and the multitude of agents implemented creates a diversity of behaviours and somehow, of opinions. Thus, through modelling, researchers attempt to formalize the specific nature of representation, as an intermediary mental object between agent and its environment. This task is not an easy one as the concept of representation itself is subject to several contrasted theories [7,8,9,10]. However two main trends may be identified; a representation is considered either as a stabilised knowledge structure, included in the long-term memory of the actor, or as a contextual building process, included in his operational memory [11]. The first approach, known as a cognitive one, states that representations are mentally built using a set of symbols and logical inferences, permanently stored and reused [12,13]. On the other hand, the constructivist approach states that individual representations are temporary constructs elaborated through social interactions and communication; thus, they are highly context-dependent [7,14].

In both case knowledge and decision-making are not fully conscious in a person's mind. Either because some of the elements and processes that constitute knowledge and representation are said to be unconscious [15] or because the nature of representation is said to be socially constructed and continuously evolving [16]. In his "background" theory, the philosopher Searle joins the same point by stating that the faculty of representing oneself depends on non-representational abilities and elements [17].

To handle the issue of modelling representations there are two approaches. The first one is to use theories that provide frameworks to model representations. The origin of these theories may come from the computer science field or from social sciences community. The second one is to try to elicit stakeholders' and implement it into a model. This approach is widely used in knowledge engineering.

2.1 Modelling from Theories

In the field of MABS there are still different postures, depending mainly on the scientific community of the researcher. A modeller or a computer scientist, working on the same issues of agent based simulation will orientate their research in the same directions but from different points of view and with different tools.

For instance, a major trend in computer science is to consider an individual representation of the world as a plan, which might be implemented at the agent level with the Belief–Desire–Intention agent architecture [18]. This provides a framework for the modeller in his formalization of elicited knowledge.

The social scientists will plea for more sounded social theories. At Mabs 2002, Jager and Janssen [19] call for "agents rules based on theoretically rooted structure that captures basic behavioural processes. Such a structure should be based on state-of-the art behavioural theories and validated on the micro-level using experimental or field data of individual behaviour". To do so, social scientists use theories of Social Sciences and attempt to adapt them into a multi-agent model [20,21]. Those efforts are encouraged by the natural modelling facility that MAS provides [22].

2.2 Eliciting from Stakeholders

The principle of Knowledge Engineering consists in asking experts to describe a system in order to model it. Information asked to experts are on: (i) how they take decisions when confronted to a problem, (ii) what information they use to take their decision and (iii) what are the operations to be done when an option is selected. Thus, the focus is on the expert's knowledge about a domain and on the way he takes decisions. The implicit viewpoint on representation is thus the cognitive approach.

We present here briefly an overview of elicitation techniques found in the literature and then present the companion modelling approach that we develop and use.

Knowledge Engineering: from Transfer to Modelling. The elicitation and modelling of the representations are two tasks tackled by knowledge engineering experts [23]. Here again, two schools of thought prevail.

The first one, called the transfer view, treats the elicitation and the modelling as two successive and independent phases. The eliciting process is made of a direct extraction of information, followed by interpretation of collected information. Extraction is achieved through semi-structured interviews, process monitoring or ethnographic surveys. These methods are highly complementary as behavioural observation may help solving communication shortcomings or misunderstanding [24]. In the Transfer view, interpretation is often made using the Protocol Analysis technique, based on the knowledge level theory [15]. The principle consists in identifying in a transcript all words and semantic expressions related to the elements and concepts that are relevant to the project. The experience of knowledge engineers using Protocol Analyses has refined and adapted the Newell's knowledge type classification. They have identified different types of, what they call, knowledge objects and associated typical semantic expressions for each of them [25,26]. Table 1 presents Milton's classification of knowledge objects [27]. Moreover, the use of Protocol Analysis by knowledge engineers has shown that it was particularly relevant for eliciting facts, rules and tacit knowledge. [28].

Table 1. Milton's knowledge object classification and associated semantic expression

Knowledge object	Semantic expression
Concepts (object, idea, person)	Usually equivalent to nouns
Instances	Ex. "my car" is an instance of the concept "car"
Processes (task, activity)	Ex. "build a house", "design the engine", "plan the project"
Attributes and values	Attribute: Ex. "weight", "cost", "age" Value (often adjectives): Ex. "120 kg", "heavy"
Rules	Ex. "If… then…", "Do… until…"
Relationships	Usually equivalent to passive verbs Ex. "…is a…", "…part of…"

Researchers following the second approach of Knowledge Engineering, called the modelling view, claim that the interpretation is strongly influenced by the implementation formalism of the model. They believe that it results in a shallow and fuzzy knowledge-based system that is hard to validate or maintain properly. In order to get round the constraints of transferring elicited knowledge into the formalism of implementation structure, knowledge elicited from experts is structured and organized through a pre-defined conceptual model [29]. In addition, several elicitation techniques are used together in order to tackle different levels and types of knowledge (e.g. tacit knowledge) as also to diminish mistaken interpretation due to the technique itself. However, one main aspect if this approach is the involvement of experts in the modelling phase (e.g. choice of the rules or objects of the model). This has been proven to reduce the biases generated by modeller's subjectivity and miss-interpretation [23]. Moreover with such an approach, experts may give feedbacks during the course of the modelling, which will enrich the model. This is why, in cognitive mapping for example, participatory model construction is said to enable capturing the full richness of stakeholders' perceptions [30].

Companion Modelling Approach. The same participatory approach is used in companion modelling, though the model here is a MABS. As opposite to other MAS representation modelling, companion modelling approach involves stakeholders in various phases of the modelling process. By building models of stakeholders' representations in a participatory way those works serves to create a shared representation and to simulate scenarios [31,32]. This combined use of MAS and participatory approaches is especially appropriate for taking into account the social construction of representations and for giving a relevant validation of the model. We separate companion modelling and participatory MAS as, on one hand involving stakeholders in the simulation stage and on the other hand stakeholders' involvement in the creation and building of a model[1].

[1] This is different from Parker's classification which defines participatory MAS as an approach involving stakeholders at any stage of the modelling process.

Companion modelling involve doing permanents loops between three stages of the modelling process: (i) observing, analysing and interpreting the real world, (ii) modelling information extracted from the real world, (iii) simulating scenarios that raises questions to be explored back to the real world. Application of this approach enables rapid feedbacks from the stakeholders about the model structure and the simulations generated. Most of the time running versions of the model from which simulations may be generated are presented, discussed corrected and/or validated by the stakeholders. Several versions of the model are thus discussed as the model construction evolves [33].

Participatory MAS suggests the use of workshops in which models are created in complete interaction with, and somehow by, the stakeholders. The model creation may start from predefined structures or not, and may use different model artefacts (computer model, role game...) [32]. However, each time the principle is the same: stakeholders design the model during the workshop through different means and researchers are facilitators in this process as well as being the modellers.

3 The Methodology Proposed

In order to reach our aim of progressively creating an emerging shared representation between actors that will facilitate dialogue among them, we needed to develop a specific methodology to go from stakeholders' representations of a system to one or several formalized models consistent enough to be used as simulation tools. Even though Knowledge Engineering techniques are attractive, we needed to adapt them in order to go up to a formalized model and to deal with actors with several tasks that are often illy defined. Moreover Knowledge Engineering tends to follow a cognitive approach of representations, which is not always fitting what can be grasped from the field of natural resources management, which we are interested in. We propose thus a methodology based on seven elements that constitute its fundamentals.

3.1 A Constructivist Perspective

We acknowledge the constructivist perspective and believe that the nature of representation is socially constructed through the people's interactions with their physical environment and their social relations. However, we assume that representations have a psychological existence in peoples' mind and thus may be elicited. That do not mean that when a person explains his view on a process for example, and especially in the context of a discussion, his words convey perfectly his representation of the process. We are aware that when a person communicates his representation, he changes it at the same time; this is also what means, "to be socially constructed". Moreover strategic behaviours may appear leading people to explain something else than what they perceive as their own representations. Therefore any elicited representation should be used as a basis for discussion rather than decision.

3.2 The Use of Elicitation

Our methodology uses elicitation techniques coming from Knowledge Engineering as a mean to access people's representations. Although individual semi-structured interviewing is severely criticised by knowledge engineers, we consider that it is the most appropriate elicitation technique for the context of our applications. When dealing with stakeholders in the context of natural resources management, interviews and meetings are common and well accepted by local actors. Moreover, we believe that the weaknesses of interviews, as seen in the Knowledge Engineering view (interpretation biases and not capable of extracting tacit knowledge), can be corrected by parallel techniques such as joint field observations, anthropological surveys or stakeholders' zoning. With the use of individual semi-structured interviews, we associate the use of Protocol Analyses as a mean to extract knowledge objects from a transcript. In this view, our assumption is that knowledge objects as presented in Table 1, are carrying in their nature and organization, peoples' representations.

3.3 Taking into Account Situated Cognition

We consider with moderate situated cognition theory[2] that representations are context-dependent [34,35]. During the elicitation process, we try to deal with this by putting the person in a context that is making sense for the topic of the representation which is addressed. For example to elicit someone's representation of a factory process, we would interview the person in the factory while the process is operating. However, in the field of natural resources management, the range of actions of a person on the system is very large, both in quantity and along the timescale. Thus, this methodology suggests that (i), as for the Transect Method allowing to extract information concerning spatially distributed processes [36], interviews should be done on the field, in a relevant location for the interviewee's actions and (ii) interviews' first question should be related to the interviewee's main actions on this location. More explicitly, in the context of eliciting a farmer's representation of his interactions with the environment, the methodology consists in interviewing him on his fields and asking him to describe his agricultural practices at first.

3.4 Modelling during the Transcript Analysis Process

In our methodology the analysis of the transcript and the modelling are merged. That means that we built the elements of the model during the course of the transcript analysis. Using transcript analysis and modelling in interaction results in a loop process. Transcript analysis helps the modelling process in identifying and designing the microstructure of the model (objects, attributes, relations...). Identification of inconsistencies or missing elements that appears during the modelling process leads the modeller to look back in the transcript for information that he didn't identify at first and that enriches the model. Thus, although a coding frame is predefined for the transcript analysis, it is progressively refined through the interaction with the

[2] As opposite to some proponent of situated cognition that denies any existence of a representation if not in relation to an object.

modelling process. Moreover, even though the transcript analysis is in someway evolutionary and going back to previous steps of the model construction is allowed, the first objects that will be modelled will have a predominant position in the model. Thus, special care has to be given to the choice of the first knowledge objects modelled.

3.5 Use of Multi-agent Based Simulation

Our main reason for choosing MABS is that it is especially appropriate for taking into account heterogeneous social representations of a system. Moreover, if we consider simulation as the variation over time of a model inputs, conditions and rules, in order to observe model outputs under different "what if" scenarios, MABS can be used to explore stakeholders' representations in a dynamic way. This exploration of the model through simulations is useful for our methodology in two ways. On one hand, it allows us to check the model consistency according to the stakeholders' authentication of its different components. Stakeholders' authentication requires that the stakeholders previously understand the implementation model. To do so, the use of model artefacts such as role games give the opportunity to explain the content of the implementation model and help the stakeholders to enter the flesh of the model [37]. On the other hand, simulations developed with MABS are very efficient communication media. As a matter of fact, MABS presented on a computer screen, displays the environment in a simple and synthetic way that can be understood by all, even people who are not familiar with computers. One of the best evidence of this is the selfCormas application where Senegalese farmers were able to discuss MABS results displayed on the screen of a laptop [32].

3.6 Participatory Model Construction

A part from being a mean to enrich the model, we believe that involving stakeholders from which we elicit representations in the model construction, will allow reducing the weaknesses of interviewing technique that are interviewers' subjectivity and miss understanding and inability to elicit tacit knowledge and representation. This is mainly enabled by the facts that (i) the building of the model (its components and structure) is always kept open to any changes suggested by the stakeholders, (ii) as being involved in the model construction, it can be assumed that stakeholders model's appropriation is enabled and makes the model more understandable to them, (iii) the fact to follow step by step the evolution of the model construction address stakeholders' reflection which results in new questions or information for the model. Applying this approach to participatory mapping for example is quiet easy to handle, however having choose the use of MAS, we had to find a way to involve stakeholders in the construction of a "more complex" and dynamic tool. In our methodology, companion modelling and participatory MAS workshops type are means to involve stakeholders in the construction of such a model. The participatory model construction is also performed at the model components level. Indeed, when a missing element of the model (as defined in paragraph 4) is identified and cannot be retrieved from the transcript, a usual solution is to perform complementary surveys and interviews. We propose here to involve the actors in the formalization process. The missing elements are replaced by a temporary formal expression that is submitted to the judgement of the relevant actors. Successive feedback interactions are used to finalize the formal expression. At this stage, there is no specific protocol of communication between the modeller and the actors; thus, one can describe the communication process as informal.

3.7 Modelling Contradictory Representations

Modelling heterogeneous stakeholders' representations often leads to contradictions between several individual representations. Moreover, individual representations are not necessarily complete or coherent with it. Our actual assumption is that individual representations are parts of a system of representations driving stakeholders behaviours at a collective level and that incorporating parts of individual representations into an overall model will tackle a wider currency among the group being studied. Thus, when elements of different individual representations complement each other we model them in a same model. Now, when contradictions are found between different individual representations it strikes us as important to handle and take them into account as they reflect the heterogeneity of social representations of the system. We have thus defined in this methodology three ways to handle them according to the nature of the contradiction. At first, contradictions may appear because two persons are referring to a same process but are not using the same indicator. As for example, one can assess soil moisture through it colour while another person will look at the aspect of the crop being cultivated. In such case differences are kept and the different indicators of the same process will be modelled in a same model using specific viewpoints. Second, when contradictions appear about the value of a threshold or of a quantitative result, we consider that further discussion with stakeholders may smoothly reach to a consensus among the different opinions. If a consensus is not reached, then the divergence is handled with the last way. This third way appears when individual representations are found to be explicitly and unambiguously contradictory. This is for example if a person believes that a process affects another process in an opposite way with another person's belief. In such case, and whatever which position is scientifically true, each view is modelled separately and the overall model is split in two separate models (all non-contradictory elements being maintained equal in the two models). When presented to the stakeholders, simulations of each model will have to be performed and discussed. Once again, discussions may lead to a consensual model or not.

4 Application to Farmers' Representations of Runoff and Erosion

The methodology was applied in 2002 to the Orb's basin (France), a case study of the Firma project [Firma: http://firma.cfpm.org]. The sub-catchment studied was the Taurou (64 km2). The issue was on vineyard fanners' representations of runoff and erosion at different scales: plot, farm and catchment scale.

4.1 Sample and Interviewing

As we were looking for diversity of representations we based our sampling on heterogeneity criteria. We chose 10 vineyard farmers according to various farm characteristics (location, wine marketing type, farm size, farmer's age, and wine quality label). Most interviews were conducted on the farmer's fields in order to cope with situated cognition theory. Interviews were individual and semi-structured. Guidelines were prepared for the interviews with four different topics, introducing questions for each topic and prompting questions. Interviews were audio-recorded and notes were taken. Audio-recorded interviews and notes were typed out verbatim in order to generate one transcript for each interview.

4.2 Transcript Analysis

In order to structure the transcript analysis and to limit researchers miss-interpretations of the text, a thematic analysis was performed previously to the modelling process. It consisted in identifying recurrent themes through a first rapid reading of all the transcripts in order to define broad topics and then by a second detailed reading of all sentences to check rather they could fit in one of the topic. This resulted in a detailed description of different themes. All transcripts' statements were then classified according to those themes and one transcript for each theme were generated. Because those transcripts were made of different farmers statements, attention was given to keep trace of the origin of the statements (which interviewee said A or B).

We then looked in the thematic transcripts, for semantic expressions that we could interpret into UML formalism (Unified Modelling Language). The coding frame which we have use was inspired from the knowledge objects classification presented in Table 1, as we found many similarities between knowledge objects and UML formalism. Those correspondences are shown in Table 2 below.

Table 2. Corresponences between knowledge objects and UML formalism

Knowledge object	UML formalism
Concept	Class
Instance	Instance
Process (task, activity)	Operations
Attribute and Value	Class attribute and Instance attribute's value
Rule	Methods
Relationship	Association, Aggregation or Inheritance

The combination of Table 2 and Table 1 shows examples of semantic expressions, which were used to define specific UML elements. However, these correspondences were not used in a strict and fix way. It was rather used as a framework to facilitate the identification of relevant information in the transcript and the coding frame evolved during the course of the model construction.

4.3 The Construction of the Model

The parts of modelling construction presented here show the co-interaction of model construction and transcript analysis. Our aim here is not to give a full description of the model but to illustrate the application of our methodology. Moreover, in this application we did not have the opportunity to promote stakeholders' feedbacks on the model yet. Thus, in this paper we show the benefit of the interaction between transcripts analysis and modelling for the modeller but not it benefit for the stakeholders.

The Starting Point. As explained previously, the resulting model is dependent of the choice of the first elements that are modelled. In this application we were looking at perceptions about runoff and erosion, moreover transcripts' first reading demonstrated that storms were always mentioned as the cause of those processes. It thus seemed natural for us to start the model construction by this object. It also leaded us to choose a model sequencing driven by storms events.

The first statement modelled was:
« If there is a too strong storm, the soil does not drink and it runs off» [Farmer A][3]
Applying our coding frame we modelled this statement as so:

- Two objects coded as classes: Storm and Soil
- One attribute of the Storm Object: "strength"
- One relationship between Storm and Soil coded as an association of the class Storm to the class Soil
- One process coded as a method of the Class Soil: runoff

We also defined the method "rain" for Storm.

Then we looked at the following statement:
« [Runoff] depends ...if it's falling strongly or slowly. If 40 mm fall in one shot, it runs off » [Farmer B]

The use of adverb "slowly" and the expression "in one shot" helped us to refine our interpretation of the word "strongly" and the expression "strong storm" that we had found in several interviews. We interpreted it as the expression of the rainfall intensity and we thus replaced the attribute "strength" of the Storm[4], by its "intensity". Moreover, the semantic expression "in one shot" refers to a length of time. We thus added an attribute "time length" to Storm.

Looking at Additional Information to Model the Runoff Method. At this stage we had some information about Storm but not as much for Soil, and thus could not define the process of the runoff method. We therefore looked in the transcripts for information that will refine the definition of Soil. We identified several statements that we modelled. We will here present the three main one.

[3] Square brackets within a farmer statement are researchers comments or details. As we respect their confidentiality, farmers names are not quoted. We indicate the origin of the statements by code letters. For now on, we will follow this codification.

[4] When referring to a object of the model we will write with a capital letter at first, as here for Storm.

« A schist, you take 100 litters of water, you pour it; the water directly infiltrates, it disappear... With a red soil, the water flows » [Farmer A]

We thus modelled an attribute « type » two Soil and defined to possible values: schist or clayey-limestone (which was the type of soil Farmer A was referring to as « red soil »). We noted that in one case infiltration was high and in the other case infiltration was low. We therefore modelled a Soil attribute "infiltration capacity" and gave two values to it: "high" and "low" respectively for schist and clayey-limestone Soil types.

Several statements such as: *« After several rains, it ends up to runoff » [Farmer F]*
This type of statements and ideas were interpreted according to what was already in the model at this stage. Several interpretations were possible and we chose the one that was supported by strong theoretical background. This is that a soil has a water storage capacity and that when the actual quantity of water in the soil has reached it storage capacity, infiltration is not possible anymore and "it ends up to runoff". Thus we added the attribute "storage capacity" to Soil and we knew that this attribute would have to be updated at the end of the runoff method.

«[On clayey-limestone soils] if it rains during summer, but not long enough, it's useless because everything runs off» [Farmer D]

Here too we had to interpret the statement. We found in other farmers' statements that a puddling could appear on soil surface during summer. Moreover, we know from theory that puddling refrains infiltration. Thus we assumed that Farmer D was referring to puddling is his statement. We thus added a "puddling" attribute to Soil that could have two possible values: true or false; and we knew that in the runoff method of Soil, if puddling attribute was true, then infiltration will be nil for short rains. Moreover, we had elicited information on the fact that puddling appears during summer and disappears after a certain length of rain (so we could assume that their was a "puddling update" method), but we had no quantitative information that would enable to model this process. Therefore, we used theoretical quantitative information and determined thresholds for our model.

The last two statements need important additional comments. We have seen here two examples of using theoretical information, or expert knowledge, in combination with farmers' knowledge. As explained in the fundamentals of our methodology, this is done in order to make it possible to be used in simulations and to be discussed by the stakeholders. Hence, this reinforces the constructivist posture announced at the beginning of our methodology, since the suitability of this external expert knowledge added to complement the model has to be checked with actors. Moreover, in both case the theoretical element added was chosen in order that it do not distort farmers' statements and that it explains them in the simplest way as possible in order to facilitate its further discussion.

At this stage the model structure was as shown on figure 1 and we had enough information to model a first version of runoff method.

To model the runoff method we looked at processes previously stated by farmers, that we summarize here:

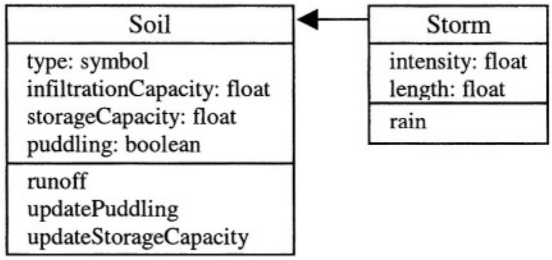

Fig. 1. UML Class diagram of the ùpdel at step 1

1. Rain generates infiltration or runoff [all farmers previously quoted]
2. If puddling is true, infiltration is nil [Farmer D]
3. If Soil storage capacity is full, infiltration is nil [interpretation from Farmer F]
4. Soil's infiltration capacity increase infiltration positively [Farmer A]
5. Rain intensity and length affects runoff positively [Farmer A and B]
6. Soil storage capacity evolves during a rainfall event [Farmer F]
7. Puddling state is changed to "false" after some time [Farmer D and theory for the threshold]

From those information, we modelled the runoff method as show on figure 2.

4.4 The Resulting Model

We have seen along the construction of step 1, how we use transcript analysis and modelling in concert, and how this help the modeller to refine both modelling process and analysis of the transcript. We have also shown, how references to theoretical information was necessary to achieve the model construction, and especially for interpretation of processes. Finally, the description of the construction of method mainly coming from elicited information suggest that modeller's interpretation induce biaises in this method. Two ways can then be used to overcome these biases: confrontation with other modellers on one hand, discussion with stakeholder on the other hand. As so, when submitting the methods created by the initial modeller to another modeller, the runoff method was the most controversary one. Handling biases through discussions with stakeholder is done through the companion modelling used in our methodology. However, for this application we did not have the opportunity yet to apply the full methodology and to receive feedbacks from the stakeholders.

The current overall model incorporates stakeholders' representations through a set of physical and social interacting objects as shown on Figure 3, as well as through various methods of farmers' perceptions of natural processes and heterogeneous Farmers' behaviours and actions on their environment according to heterogeneous objectives and viewpoints.

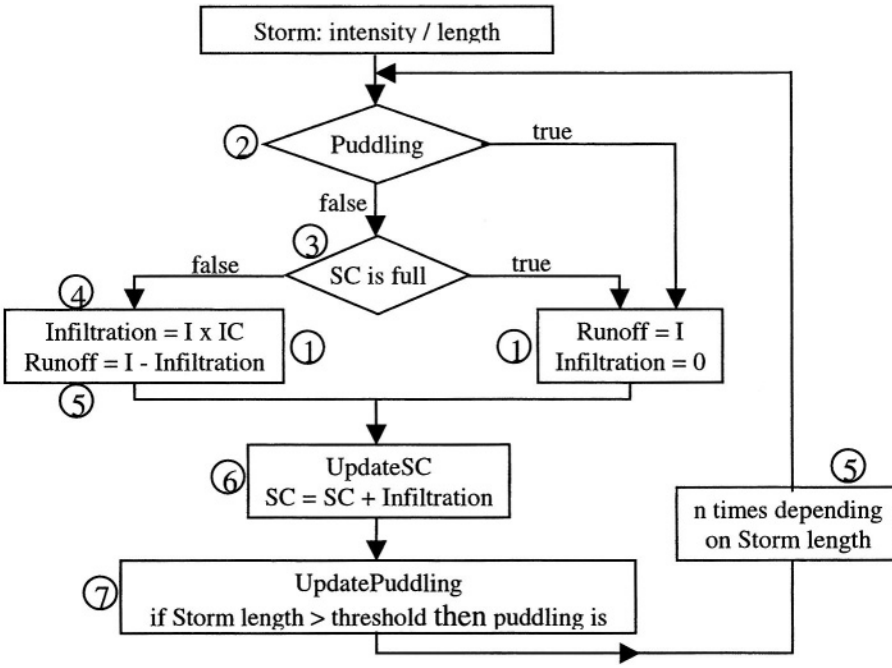

Fig. 2. UML Activity diagram of the Runoff method of Soil. Numbers in circles refer to the summarized farmers' statements numbered above. I stands for Storm intensity, IC stands for Infiltration Capacity, SC stands for Storage Capacity

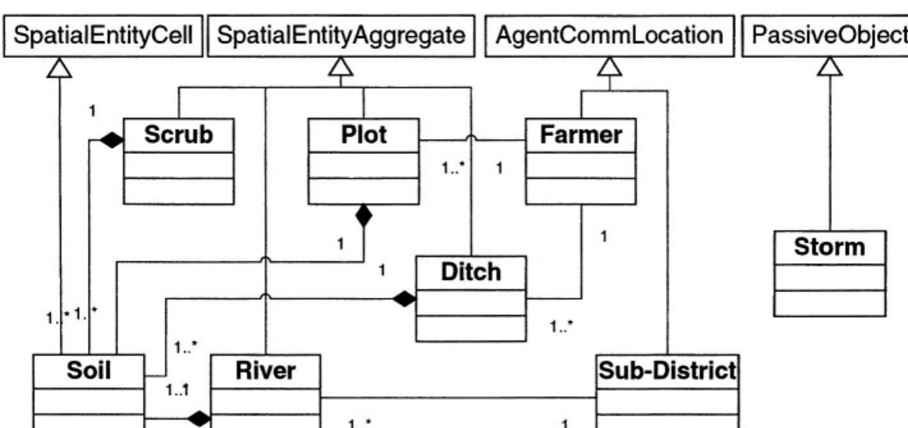

Fig. 3. UML Class diagram of the resulting model

5 Perspectives and Issues to Be Addressed

The research we are doing on modelling of stakeholders' representations leads to the need of interactions with the researchers in computer sciences working on knowledge engineering and MAS. It is a two ways interaction that may benefit both for the two communities.

5.1 How Can Knowledge Engineering Be Used to Provide Methods to Feed Agent-Based Models?

In order to handle conflicting opinions found when eliciting several experts' knowledge attempts have been tried by knowledge engineers to understand the nature of those conflicts. For example, repertory grids[5] may be used to show up similarities and differences among different opinions [38]. By comparing the repertory grid of several experts, the SOCIO tool defines four different categories of similarities and conflicts: (i) consensus, (ii) correspondence (different terminologies for a shared concept)[6], (iii) conflict, (same terminology but for different concepts)[7], (iv) contrast (different terminologies for different concepts) [39]. From this comparison the SOCIO tool aim to promote understanding between different experts in order to facilitate discussion among them and help them to define a consensual representation. Easterbrook follows a different approach and sees conflicts as "differences that matters" [40]. His approach is to elicit and model all different viewpoints in order to compare them. The comparison is mostly exploratory and conflict resolution is let to the users choice in the final stage of the process. Thus, knowledge engineering, which was at first working with a single expert, starts to propose ways to deal with several experts and their conflicting opinions by proposing sophisticated negotiation methods to the experts in order to smoothly reach a consensus among the different opinions. The trend of recent approaches consists in keeping the conflicting views until the last steps of the modelling process as differences and heterogeneity is found to enrich discussions among stakeholders.

Even if being another way of eliciting knowledge from the stakeholders, the methodology we propose also aims to keep conflicting representations in the modelling process. The use of MAS allows to handle representations' heterogeneity and some solutions have been proposed when conflicting opinions are encounter. However, more diverse and refined ways should be defined to tackle this issue of conflicting representations and we believe that interactions with computer scientists working on knowledge engineering could provide these means.

Moreover, the methodology proposed leads to the design of consistent representations at least at the collective level, entailing to transform it in simulation tools. The correspondences between raw material coming from open discursive interviews and UML diagrams allow proposing a frame for participatory Agent Based

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[5] Repertory grids classify perceived elements of a domain according to bipolar dimensions characteristics. They identify major distinctions and terminologies of a domain representation.

[6] Terminology has to be understood as the explanation of a concept by the interviewee.

[7] The conflict emerge because we cannot determine from the terminology which concept to model.

Modelling (ABM). However the important involvement of modeller interpretation in the analysis has to be taken in account and its impact in the resulting model further explored.

5.2 How Can MAS Models Be Used to Improve Knowledge Engineering Techniques?

The use of MAS techniques can be useful for knowledge engineering. When used as a mean for discussion support and representation sharing, ABM, associated with companion modelling, allow dealing with the constructivist perspective of representation at the individual level through the acceptation of gaps in individuals' representations. The synthesis of individual representations within an ABM which aims at providing a basis to share representations is filling identified gaps of each individual's representation through completing one another and then adding external expert knowledge if required. The mixing of incomplete representations is the modelling counterpart of situated action viewpoint on representations and plans which is considering that it is the game with plans and around plans which is interesting for action [41]. Individual representations are more resource than determining elements for action as well as for dialogue. However such mixing of representations is relevant only for our aim of discussion support. Whenever understanding behavioural patterns is concerned, gaps are key pieces of information by themselves. The context is then of a scientific learning while other posture is more of social learning. ABM and companion modelling approach are providing in that context a "constructivist" knowledge engineering technique.

Moreover, the Object-Oriented approach used in MAS is a relevant framework for Knowledge Engineering to model knowledge-based system. On one hand, during the modelling phase Object-Oriented structure, which is very similar to the way people express concepts, helps to structure the elicited knowledge. On another hand encapsulating experts' knowledge into objects is very useful as it may benefit from the reuse feature provided by Object-Oriented approach [42]. This can easily be linked to already existing elicitation and modelling techniques used by knowledge engineers. For example, the hierarchical node structure of the Ontology approach is very similar to the inheritance of classes of Object-Oriented language [43]. Connections between nodes of a semantic network representation can be modelled through interactions among objects in a MAS. Similarly, as we have done in our methodology, the same kind of analogy can be used with Newell's knowledge levels theory and its related knowledge objects.

Finally, Agent-based models can provide additional concepts and tools to object orientation. First of all it is one objective of MAS to simulate the interactions and negotiations of agents which have different perceptions. For a long time, work on common plans for instance form the core activity of some MAS researchers. Furthermore, Drogoul states autonomous agents can be advantageously used in the process of participatory simulations. "if they are provided with adequate learning capabilities they may then autonomously adjust or acquire their behaviour through repeated interactions with their user. The kind of learning procedures are being actively investigated in many sub fields of Artificial Intelligence. The agent may learn its behaviour in situation and in a progressive way" [6].

The participatory simulations we propose are a way of eliciting knowledge from the stakeholders, as shown in this paper. This work requires the use and development of concepts and methods of both the field of knowledge engineering and MAS. As most of the implementations of the agents in social sciences come from theoretical social models, these interactions have not been very fruitful until now. With the objective of creating models of the observed world, it seems to us that this encounter is necessary and we are confident that this will open a new theme of research in MABS community.

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Modelling a European Decision Making Process with Heterogeneous Public Opinion and Lobbying: The Case of the Authorization Procedure for Placing Genetically Modified Organisms on the Market

Juliette Rouchier[1] and Sophie Thoyer[2]

[1] GREQAM, CNRS, 2 rue de la Charité,
13002 Marseille, France
rouchier@ehess.cnrs-mrs.fr

[2] LAMETA, ENSAM-INRA, 2 place Viala,
34060 Montpellier, France
thoyer@ensam.inra.fr

Abstract. The paper presents a multi-agent model simulating the European decision-making procedure for authorizing the placing on the market of Genetically Modified Organisms (GMO). The model illustrates the political links between public opinions, lobbying groups and elected representatives at the national scale and at the European scale. It compares the procedure which was defined by the European 1990/220 Directive in 1990 with the new procedure which has replaced it in 2001 when the 2001/18 Directive was voted. The objective is to explore the impact of the innovations of the new Directive on the lobbying efficiency of NGOs and biotechnology firms and to assess if Multi-Agent simulation can help to improve our understanding of collective opinion and political markets dynamics.

Keywords: Multi-agent simulation, agent-based simulation, lobbying, decision process, Europe, GMO

1 Introduction

The paper presents a simulation model designed to provide a better understanding of political decision-making procedures implying several interacting agents (decision-makers, voters and pressure groups) with heterogeneous preferences. We chose the example of the European Union procedures for authorizing the release of GM-crops into the environment and the placing on the market of GM-products. Our objective is to compare two collective decision procedures: the first one, which came into effect in 1990 (90/220 EC Directive), is based on a fairly straightforward procedure of qualified majority voting by the European Council of environment ministers. The second one, which replaced the first one and came into force in 2001 (2001/18 EC Directive), implies a several step process with public consultation, conciliation meetings and final unanimity voting by the European Council. It was undertaken with the objectives of: improving the participation of the public in the decision

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process and achieving a more stable consensus between European countries on the level of required regulation. The logic underlying the new regulatory framework was that a more "democratic" decision process at the European level (in terms of transparency, participation and voting procedures) would secure the public acceptance of GMOs.

Our model was built in order to test whether the changes in the decision procedure are compatible with the objectives stated. The simulations are conducted with three purposes: (1) to explore different scenarios of lobbying strategies by biotechnology firms and environmental NGOs and to compare their relative efficiency; (2) to evaluate whether the 2001 procedure leads to final collective decisions which reflect better the diversity of public opinions in nation states, (3) to assess to what extent the 2001 procedure may be more successful than the 1990 procedure in inducing changes in public opinion and potentially more convergence between heterogeneous national opinions.

The first section of the paper describes the European regulation for the release of GM-products. The second section describes the multi-agent based model structure and the artificial societies which were created with this model. The third describes and comments our simulation results. It shows that the switch from the 1990 Directive to the 2001 Directive increases the influence power of NGOs. Within the architectural framework of our system, it means that the 2001 Directive improves the coherence between national public opinions and the final European decision. However the 2001 procedure does not succeed to improve homogeneity among European public opinions. As a conclusion, our model is –to our knowledge- the only agent-based simulation which seeks to model the political market between voters, elected representatives and lobbying groups and which includes a supra-national dimension. It proves to be helpful for the analysis of the lobbying strategies within a complex political environment.

2 Modelling the European Regulation for GMO Release

Regulation

The aim of the 90/220 Directive of 23 April 1990 was the harmonization of procedure and criteria for biosafety assessment under the concept of the European single market. The Directive (transposed in all EU member states since 1995) sets a number of constraints for companies intending to manufacture, import or grow a GMO in a European country. They must request approval from the official biosafety authority of the state concerned by submitting a notification to the national authority containing detailed information about the GMO and a preliminary risk assessment. The national biosafety authority must take a decision within 90 days following the notification. It conducts then a risk assessment and either rejects the demand or approves it. In the latter case, the member state must forward all relevant information to the European Commission. The Commission then notifies and distributes the information to all the other member state biosafety authorities. Other member states are given 60 days to react; if at least one member state objects to the approval of the GMO, then a European regulation committee made up of representatives from all the member states is formed to analyse the case. This committee votes on a qualified (weighted) majority basis on whether to approve the GM0 or not. If a qualified majority[1] is obtained, the authorization is granted within three months by the council of Environment ministers and applies then to all member states: country members are theoretically not allowed to forbid the GMO on their own territory. If the authorization demand is rejected, then no authorization for this GMO is provided in any EU countries.

It has to be underlined that each authorization procedure since 1990 has given rise to sharp debates, in which both anti-GMO associations and biotech firms tried to push forward their position. Overall public opinion in the European Union has become increasingly suspicious of GMOs [1]. Such reluctance has been partially shaped by powerful environmental non-governmental organizations (NGOs), consumers unions, and some farmers unions, which have been very vocal, financing anti-GMO campaigns, lobbying actively in Brussels and even taking direct anti-GMO actions (demonstrations, destruction of genetically modified maize fields etc.). NGOs such as Greenpeace and Friends of the Earth Europe have made GMOs one of their top priorities for their actions in Europe since the end of the 80's. They have formed solid alliances with consumer groups (such as the European Bureau of Consumers' Unions) and with farmers unions. They were successful in transforming the GMO issue "into one of high saliency and - in the eyes of the wider public- of low complexity", therefore "increasing the public distrust in regulatory authority" and reinforcing their influence on decision-makers [3]. On the other hand, the biotech sector is concentrated and organized [6]. US and European biotechnology companies have sought to obtain softer regulations on market access and have based their advertising campaigns towards the general public on the arguments that GMOs can improve productivity, can contribute to preserve the environment, and can help to cure diseases. They have also defended their positions by lobbying at a more political level, reminding governments that they contribute to create value added and are a powerful economic sector, whose competitive capacity should not be jeopardised by unjustified controls and regulations.

However, despite the lobbying of biotech firms, a number of European governments felt the pressure of public opinion and chose to restrict unilaterally the release of certain GMO[2]. Since April 1998, there was a *de facto* moratorium on new approvals, on grounds of potential hazards to human health and the environment. By then, only 18 GMOs had been approved by the EU. The biotech industry claimed that it was a "victim of biopolitics" [16], and that "the public perceptions of modern biotechnology were having an effect on the public policy process which in turn was causing changes in the regulatory guidelines". New discussions were launched from 1998 for a revision of directive 90/220 in order to extend and clarify its scope and to tighten GMO control. The objectives were threefold: "to improve the administrative procedures; to harmonize decision-making between member states on the basis of common principles of risk assessment; to improve the flexibility of directive

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[1] The qualified majority requires a minimum of 62 votes. The voting weights within the EU are the following: France, Germany Italy United Kingdom: 10 votes; Spain: 8 votes; Belgium, Netherlands, Greece and Portugal : 5 votes; Austria and Sweden : 4 votes; Ireland, Denmark, Finland : 3 votes; Luxembourg : 2 votes.

[2] The dispute was triggered by the approval by the EU of a variety of Bt-corn produced by Novartis (1996) and Monsanto's Roundup Ready soybean (1996) for which scientists had expressed serious doubts concerning their health and environment immunity.

90/220/EEC while maintaining a high level of protection for human health and the environment" *(ref COD/1998/OO72)*. The Directive 2001/18 /EC, repealing the 90/220/EC Directive was finally voted in March 2001: it included the gradual elimination of antibiotic resistance markers in GMOs; tighter risk assessment carried out prior to authorization; tighter time-limited consent[3], renewed voting procedures and consultation of the public.

The procedure for obtaining the authorization to place a new GMO on the European market is more rigorous: a notification must be submitted to the national competent authority of the Member State where such a GMO is to be placed on the market for the first time. The competent authority produces an assessment report which indicates whether the demand is accepted or rejected. In the acceptation case, the information is transmitted to the competent authorities of the other Member States. The Commission also makes available to the public the information concerning the GMO. In the absence of any reasoned objection from a Member State or the Commission, or if outstanding issues are resolved through discussions between the competent authorities, consent is given to the notifier. In case when an objection is raised and maintained, the Community procedure is the following: the Commission seeks the opinion of the Commission Scientific Committee. If unfavourable, the notification is rejected. If favourable, then a European regulation committee is set up with representatives of the Member States in order to find a conciliation solution on the basis of qualified majority voting. When no qualified majority is obtained for authorization, the final decision is taken by the Council of Ministers after consultation of the public. Authorization requires unanimity.

3 How to Model the European Decision-Making Procedure?

European policies are shaped by a complex policy network involving not only elected representatives (in the European Parliament) and national decision-makers (in the European Councils) but also a broad range of non state actors including nominated members of the European Committees, bureaucrats and experts of the European Commission, and various sorts of lobbies and pressure groups. A number of social science studies analyse how the multi-level European governance structure has favoured the intervention of non state actors at different phases of the decision-making process and how lobbying actions impact on European decisions [4, 18].

The biotechnology regulatory framework is an interesting case study which was analysed by social scientists and political economists, mainly to compare European and US policies, and to analyse why they seem to diverge so drastically on the definition and implementation of the precautionary principle [3, 8, 15]. It is emphasized in most papers that culture, history and institutions have shaped two different risk societies. But it is also stressed that the nature of the political markets between voters, pressure groups, and elected representatives, both at the national level and at the confederal levels is instrumental in explaining the regulatory choices made respectively by the US and the EU. Bernauer and Meins [3] explain that European biotech-critical NGOs were capable to increase their collective action capacity and to overpower the GM-producer coalition by creating a strong sense of "public outrage"

[3] The first-time consent for a release of GMOs is limited to a maximum of ten years.

and by taking advantage of the multi-level European governance system to lobby at different levels of the decision process. However, notwithstanding the quality of these studies, no framework model is available to analyse in more depth the interactions between interest groups, evolving public opinion and decision-makers at the European level[4].

We chose to build an artificial "European Society" within a Multi-Agent System to represent the European decision procedure concerning environmental issues and more specifically GMO control.. This type of simulation is often used to study complex interactions taking place between different types of agents whose representation of the universe evolves in time [10, 19, 21]. It provides a modelling environment for public choice analysis [2, 20] by allowing different levels of decision-making, and their interactions through political influence to be integrated in a single framework. The creation of a model is much more flexible that with game theory tools. They have also been used to study negotiation, as a theoretical issue [9, 17], as well as in the context of political decision-making (e.g.: Bousquet [5] on decision-making in fisheries).

4 The Structure of the Model

A Multi-agent Based Model

In this section, we describe the two simulation models reproducing artificially the two decisional processes (1990 Directive and 2001 Directive) for GMO approval or rejection.

There are four types of agents in the model: Public opinions, NGO, Firm and Decision-makers. There are 15 public opinions, characterizing the 15 European countries, and 15 related Decision-makers. National Decision-makers vote in the European Council of environmental ministers: their vote reflects the general opinion in their country but we make the assumption that they are also influenced by the lobbying of firms and NGOs[5]. The opinion of the population also evolves under the influence of NGOs and firms and is qualified by a real number between 1 and 5(1 expressing anti-GMO feelings and 5 expressing a favourable opinion of GMO; 3 is considered as an indifferent opinion). Firms and NGOs have different lobbying strategies to influence public opinions and decision-makers.

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4 Most political economy models focus on the stability of coalitions between country members or on the European voting procedures ([11]; [13]; [14] ; and many more)

5 This reflects the political economy literature on the voting behavior of elected officials, which is often analyzed in the context of a principal-agent model. The elected representative is the agent of the principals (the constituents) who elect him but the potential for « shirking » exist [12]: he can fail to maximize the utility of constituents in order to fulfill personal political preferences, for example preferences for a strict or lax enforcement of the precautionary principle. This is captured in our model by the his sensitivity to Firm lobbying relative to NGO lobbying.

Lobbying

The NGO and the Firm invest in lobbying campaigns during the decision-making process, or as a reaction when a decision has been made, that they judge non satisfactory. The NGO and the Firm are given a lobbying capacity reflecting the effort they are able -or willing -to put on the GMO issue. This effort could be measured by the financial and human means they allocate to lobbying. It is represented in our artificial system as an index, from 1 to 30, and is interpreted as the number of lobbying campaigns the lobbyist engages into at each time-step. A lobbying campaign is either directed at a Decision-maker (lobbying in the ministries for example) or at a Public Opinion (organizing demonstrations, publicizing events in the media etc.): we assume that the NGO tends to try to influence public opinion first, whereas the Firm will try to influence the decision-maker first.

The lobbying strategies of firms and NGOs is not well documented, although a number of authors have tried to characterize them . Following the findings of the empirical literature [7, 22], we chose to add another layer of complexity by assuming that the NGO and the firm have two potential strategies for lobbying[6]: they can decide to influence in priority those (Public opinions or Decision-makers) who are on their side - in order to reinforce their support- or they can decide to influence those who have opposite opinions - in order to mitigate their counter-balancing effects in the political game or even in order to bring them back on their side[7]. In both cases, their choice is to influence first those whose opinion is closest to 3, which is the "neutral" value: the underlying rationale is to ensure that allies do not cross the line and that opponents are rallied. We hence assume here that there is no random choice for lobbying actions except when two countries have exactly the same opinion.

It has to be highlighted that we have not included the role of the European Commission in our model: the political neutrality of the Commission does not necessarily mean that it has no momentum but since the final decision is in the hands of Decision-Makers, we considered that lobbying impact could be analysed at the political level only.

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6 The rationale for adding it is to mitigate the effect of the simplifying assumption we made in the model structure by introducing only one Firm and one Public Opinion. In fact, the real political market is characterized by numerous biotech-critical associations and numerous pro-GMO firms, located in different European countries. It is interesting to test what are the outcomes of the political game when the most active anti-GMO associations tend be created in countries whose public opinion is sympathetic to GMOs (a strategy where NGO concentrate their lobbying activities towards pro-GMO countries) or when anti-GMO NGOs are created in countries whose public opinion is suspicious of GMOs (a strategy where NGO concentrate their lobbying activities towards anti-GMO countries). The same reasoning applies to biotech firms : are they more susceptible to lobby the governments from which they depend, which will certainly be more sympathetic to their economic arguments, or will they try to lobby in the countries where the biotech sector is weak or absent ?

7 For example, if the NGO's strategy is to focus at opponents: it will first campaign towards Public Opinions which oppose GMOS. Then, if it has not used up the number of available lobbying campaigns, it will lobby Decision-makers who oppose GMOS in their vote, then Public Opinions which accept GMOS and eventually Decision-makers who accept GMOS. This "allocation process" ends when the number of campaigns it is allowed to organise at each time step is used up (between 1 and 30).

Changes in Public Opinions

The opinion of the population depends both on its sensitivity to Firm influence relative to NGO influence and to the relative lobbying efforts of Firm and NGO. The opinion is such that: 1 <= opinion <= 5, with:

Change = (Advertising from the Firm * sensitivity to Firm) - (Advertising from the NGO * sensitivity to NGO)[8] (1)

And then:

opinion = opinion + Change (2)

If a Public Opinion has a high sensitivity, it means that the population is receptive to NGO arguments and actions. Depending on the simulations, the value of the sensitivities can be either all equal, or randomly chosen, or given according to the estimated values in Europe[9]. The initial values of opinion are equal for all countries (a series of previous simulations has shown that the initial value of opinion was not a crucial element for the evolution of the system) but evolve in time independently.

Decision-Maker's Expressed Opinion

If the decision-maker was not submitted to direct lobbying by firms and NGOs, we would make the assumption that his opinion is simply the opinion of the country he represents. But he is also quite sensitive to the direct influence of lobbies and therefore his expressed opinion (Eop) in the vote includes this influence. We chose to model it simply, as a value: 1 <= Eop. <= 5

Influence = (Advertising from NGO * sensitivity to NGO * random) - (Advertising from Firm * sensitivity to Firm * random)[10] (3)

Influence > 0 then Expressed Opinion = Opinion + Influence (4)

Then, the Decision-maker just votes either for or against the GMO with the following decision-rule:

- If EOp > 3 then he votes in favour of the authorization of the GM-product (YES)
- If EOp <=3 then he votes against the authorization of the GM-product (NO).

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8 Sensitivity to Firm = 1 – sensitivity to NGOS. The random element, of value between 0 and 1, is added in order to express that we deal with the « tendencies » of the representation, but not an absolute determinism.

9 Based on several criteria, like (1) the cultural and historical background of different European countries concerning risk, (ii) the relative weight of NG0s and biotech firms (iii) the institutional set-up to take into account public opinion, one can identify qualitatively three groups: very sensitive to anti-GMO lobbying (Austria Denmark France Germany Italy), fairly sensitive to anti-GMO lobbying (Belgium Finland Luxembourg Spain Sweden The Netherlands) or rather indifferent to anti-GMO lobbying (Greece Ireland Portugal United Kingdom).

10 Sensitivity to Firm = 1 – sensitivity to NGOS. The random element, of value between 0 and 1, is added so that to express that we deal with the « tendencies » of the representation, but not an absolute determinism.

Decision Making Process

In the model, two different decision-making processes can be used, “Vote 90” and “Vote 2001”, both inspired from the two deliberative process that are defined in the Directive 90/220 and 2001/18 respectively, can be found on Figures 1 and 2. For both procedure, several steps occur during which there are two ways of counting the expressed votes:

- with unanimity (or veto power): each time one decision-maker votes against GMOS, the negotiation procedure has to go on,
- with the weighted vote system, the decision requiring qualified majority (see footnote 1).

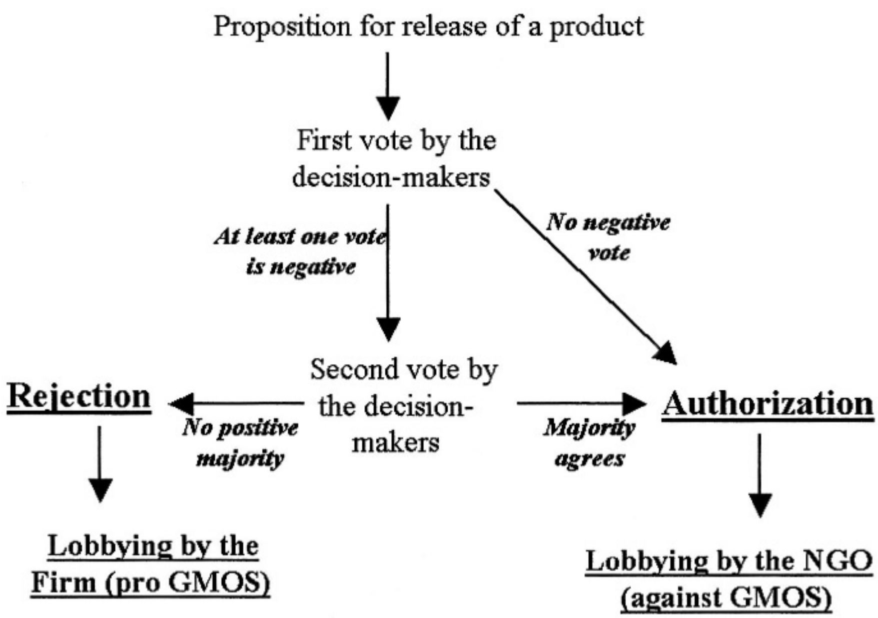

Fig. 1. Translation of the 1990 procedure for the multi-agent model

5 Model Results

Simulation Protocol and Observation Protocol

Simulating scenarios in the artificial society is for us the way to test the coherence of the interactions we have described in the system, and to compare the behaviour of the assumed dynamics with real data. In order to study the simulation, we have to observe

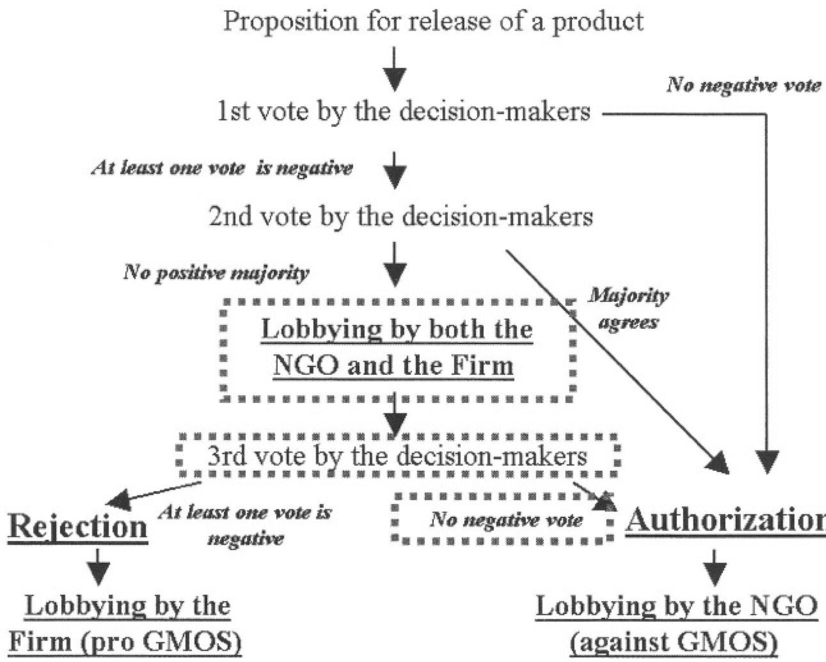

Fig. 2. Translation of the 2001 procedure for the multi-agent model. In red are indicated the differences between both processes

the evolution of some specific data along the simulation and understand these changes in correlation with the assumptions we make. Among all the assumptions, some of them are going to be tested by changing only one parameter in the whole society and see the influence of this change on the relevant indicators. The correlation we can discover through these tests can allow us to draw conclusions on the structure and dynamics of the model we built, and then to understand better the system that has been modelled.

In the simulations described below, both lobbies can perform 20 campaigns, knowing that the maximum could be 30: one for each country and decision-maker. Most of the simulations display very little sensitivity to initial public opinion, that varies from 1 to 5.

There are three main factors which describe a simulation:

- the European procedure (either **vote 1990** or **vote 2001**);
- the lobbying strategies adopted by the NGO: to influence its allies **(Anti-GMO)** or its opponents **(Pro-GMO)**
- the lobbying strategies adopted by the Firm: to influence its allies **(Pro-GMO)** or its opponents **(Anti-GMO)**

We want to observe three main indicators in each simulation:

- the number of demands for GMO release which are accepted as compared to the number rejected.

- the convergence or divergence of public opinions: average opinion and its standard deviation
- the satisfaction of public opinion regarding the outcome of the decision: number of countries which are opposed to the given decision.

Specific Patterns of Our Artificial Societies

Simulations were led for 100 time-steps, although most of the results seem to stabilize after 25 steps, and opinions and sensitivity are initialized randomly. Three general patterns can be observed, which allow us to draw a typology of our artificial societies (se tables 1 and 2)

No Authorization

In some cases, there are no or very few authorizations. The countries are split into two groups, with extreme opinions (around 1 and around 5). The size of each group is directly linked to the value of the initial opinion, and can vary from 5 to 10 countries. Average opinion and standard deviation of opinions depend on the size of the two groups. In some settings, most European countries agree with the introduction of new GMOS (9 or 10 countries), but the existence of very extreme opposing countries is enough to impose a veto.

Cyclical Authorization

In some simulations, there are regular decisions, one every two to six time-steps, which means that 8 to 14 authorizations are given in the last 25 steps. The cyclical property is also noticeable in the evolution of the opinion: the average opinion oscillates between 2 and 4, the standard deviation is between 0.25 and 0.8. There are on average 7 to 9 countries where the public opinion is satisfied. Although the majority is on average against GMOs, some votes are in favour of authorization because their public opinion, very close to 3, and can therefore be influenced towards 4.

Rare Authorization

Some simulations exhibit occasional acceptations: they can be very rare or take place quite often, but in any case they display no regular pattern. In this cases, two groups appear and are stable. The number of satisfied counties is usually close to 9 since less than 5 countries are pro-GMOs.

Table 1. Global image of societies produced with "vote 90"

Strategies	NGO strategy: focuses on pro-GMOS	NGO strategy: focuses on anti-GMO
Firm strategy: focuses on pro-GMOS	**No authorization**. Two stable groups of countries after the 20. time-step.	**No authorization** if initial opinion <= 4. **Rare authorizations** if initial opinion is >= 4.
Firm strategy: focuses on anti-GMO	**Cyclical authorizations**. Constant evolution of opinion	**Cyclical authorization**, where more than 12 countries are against GMOs.

Table 2. Global image of societies produced with "vote 2001"

Strategies	NGO strategy: focuses on pro-GMOS	NGO strategy: focuses on anti-GMO
Firm strategy: focuses on pro-GMOS	**No authorization**. Two groups of countries with extreme opinions, from 5 to 10 members depending on the initial opinion.	**No authorization**. Two groups of countries with extreme opinions, from 5 to 10 members depending on the initial opinion.
Firm strategy: focuses on anti-GMO	Either **No authorization** or **cyclical authorization,** depending on the sensitivity to firm.	Either **No authorization** or **rare authorization** when initial opinion >= 4. Two groups of countries, one with opinion around 1 and one with opinion close to 3, with maximum 5 of them being pro-GMOS.

6 What Do We Learn from the Model?

The results above help us to ***clarify*** the nature of the correlations between lobbying and final decisions which underlie our modelling choices. First, although random elements have been reduced to the minimum, there are still possibilities of getting a different outcome, starting with the same initial situation[11]. Second, the average value of opinion is not a perfect indicator of the final decision because the vote is a dichotomous choice. For example, it is possible to have a vote in favour of GMO with an average opinion close to 2: this is the case if we have 52 pro-GMOS votes from countries with an opinion just above 3 and 35 anti-GMOS votes from countries with

[11] This is due to the fact that at one specific time-step, several countries can display the same level of opinion: lobbies will therefore pick randomly which one they will influence first. It can make a real difference when opinion is close to 3.

an opinion of 1. Eventually, as shown by the table 3, the values of initial opinions do not have any impact on the final decision after a few rounds. However the initial sensitivity to Firm/NGO lobbying is important: we observe a positive correlation coefficient between the weighted sensitivity to firm and the level of average final opinion (Table 4).

Table 3. Correlation coefficients between initial opinion and average final opinion for each procedure, as a result of 50 random choice of initial sensitivity and opinion. For each sets of initial parameters, 10 simulations are run and calculation are made on the average value.

Voting procedure	Correlation (initial opinion, average final opinion)
1990	-0.105
2001	-0.064

Table 4. Correlation coefficients between weighted average sensitivity to firm lobbying and average final opinion for each procedure. The simulations are the same as in table 3.

Voting procedure	Correlation (average sensitivity to firm, average final opinion)
1990	0.627
2001	0.774

When both lobbies have the same strategies (they both have a Pro-GMO priority or an Anti-GMO priority), their interactions lead to a "no authorization" society. This shows that the action of NGOs is more efficient than the action of firms because NGOs focus in priority on the public and therefore have a long-term impact on public opinion changes. The effect of their lobbying is "memorized" by the model. On the other hand, since the Firm targets decision-makers, its lobbying efforts are only useful for one round of negotiation and have no long-term effects. This fits well with the reality since decision-makers and bureaucrats are elected or nominated only for short term (and not necessarily renewable) mandates.

Another finding is that the most efficient strategy – for firms and for NGOs – is to target the adverse parties (Anti GMO for firms and Pro-GMO for NGOs): in fact the strategy consisting in investing in the "allied countries and decision –makers" in order to stabilize their support is particularly wasteful in the case of firms since it does not bring any long-term benefits.

Consistency with Real Facts

In a second series of simulation we used the estimated values for the sensitivity[12] to firm lobbying of the European countries. The outcome is striking. In most simulations, there are no authorizations. There are a few rare cases of cyclical authorizations with the 1990 vote procedure. It happens when:

- Whatever the initial condition, the NGO's strategy is pro-GMOS and the Firm's strategy is anti-GMOS.
- Whatever the initial condition, the NGO's strategy is anti-GMOS and the Firm's strategy is also anti-GMOS.
- In rare cases: if the average initial opinion is 5 and both lobbies adopt a pro-GMOs strategy. The simulation is not absolutely determinist because a lot of countries have the same opinion and hence both lobbies can pick randomly among them.

This can be explained by the fact that in the "real" situation, countries which are pro-GMOS are in majority countries that have a small weight in votes.

Comparison between the 1990 and the 2001 Voting Procedures

The following statistical analysis is a comparison of the 1990 and 2001 Directives. The objective is to assess whether the implementation of the 2001 Directive does achieve its underlying objectives, that is to make collective choices concerning the authorization or rejection of GMOs which can be considered as more "democratic" and to secure a more homogenous opinion at the European level through concertation and multi-level voting procedures. Within this perspective, we used the model to explore two questions:

1. Are public opinions better respected in the 2001 procedures?
2. Does the 2001 procedure contribute to smooth out opinion heterogeneity between countries?

The following simulations were conducted using the same initial parameters (initial public opinions and sensitivity to firm/NGO lobbying) both in the 1990 and in the 2001 voting procedure. At each time-step, societies are different, but they emerge due to similar rules and similar initial condition. Hence what we show is that the 2001 procedure is better to create a society where opinions could be more satisfied. They allow us to compare the final outcomes – when the society patterns have stabilized – in the two procedures.

[12] It is not interesting to run simulations for estimated values of Public Opinions in the 15 European countries since we have shown that the simulation results are independent of initial opinions after a few runs.

Are Public Opinions Better Respected in the 2001 Procedure than in the 1990 Procedure?

It was shown that the 1990 procedure is such that a GM-product can be authorized although the weighted average opinion within Europe is actually against it (inferior to 3). The 2001 procedure was set up in order to reduce the gap between decisions and opinions.

Figures 3 and 4 show that, whatever the initial level of average public opinion and the average level of sensitivity to firm/NGO lobbying, the number of satisfied countries (countries for which the final European decision to authorize or reject a GM-product is in conformity with its opinion) is statistically higher in the 2001 procedure than in the 1990 procedure.

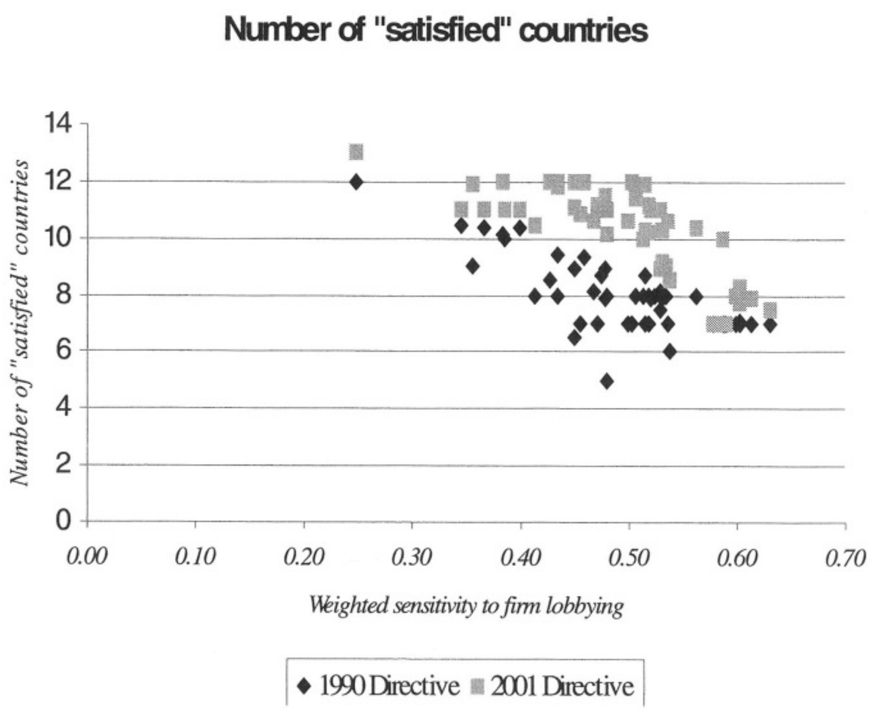

Fig. 3. Gaps between opinion and decision in the 1990 and 2001 Directives for different levels of sensitivity to firm's lobbying (each dot indicates the average over 10 simulation of the same type of the average number of satisfied countries).

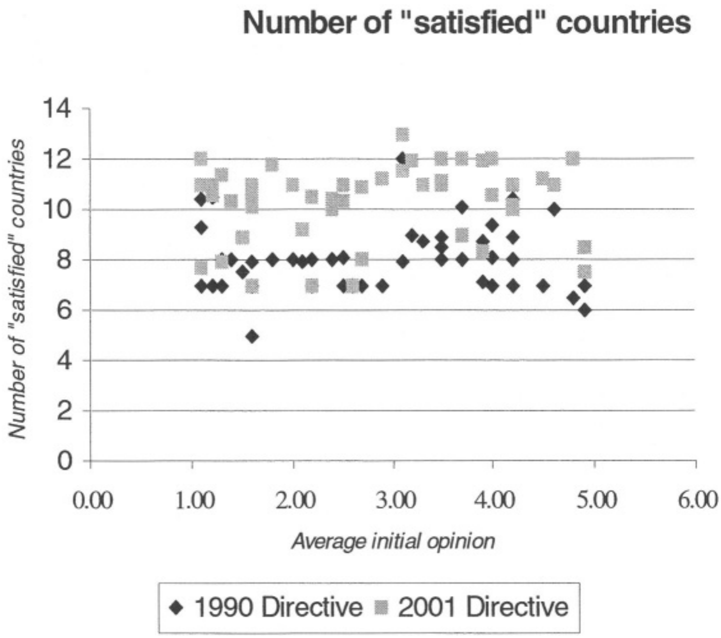

Fig. 4. Gaps between opinion and decision in the 1990 and 2001 Directives for different levels of average initial opinion (each dot indicates the average over 10 simulation of the same type of the average number of satisfied countries).

What Is the Pattern of Opinion Change under the 2001 Procedure: Does It Induce a Shift in Public Opinion in Favour of GMO? Do National Opinions Tend Converge or Does the Procedure Tend to Increase Heterogeneity of Opinion between Countries?

Table 5 shows that, whatever the NGO's strategy in the 1990 and in the 2001 voting procedures, the average final opinion under the 1990 voting procedure is higher than under the 2001 procedure, except when the NGO was following a pro-GMO strategy under the 1990 procedure and an anti-GMO strategy under the 2001 procedure. Our simulations also reveal that the difference declines when the weighted average sensitivity to firm lobbying increases. It therefore shows that the 2001 procedure gives the NGO more capacity to lobby and to induce a long-term shift of public opinion against GM-products : in effect, the 2001 procedure, which includes a phase of consultation of the public and therefore gives the opportunity to lobbies to indirectly influence the decision, is more advantageous for NGO's lobbying since it has longer term effects than Firm lobbying. However, the comparison of different combinations of lobbying strategies also shows that the Anti-GMO strategy (consisting in focusing in priority on anti-GMO actors) is more efficient than the pro-GMO strategy since the NGO, by switching from a pro-GMO strategy to an anti-

GMO strategy (comparison of columns 1 and 3) succeeds in increasing the opinion change between 1990 and 2001. The negative value in column 4 row 1 indicates that the choice of lobbying strategies for NGOs has actually more effects on average opinion change than the change in voting procedure. This seems to indicate that NGOs should maybe spend more time rethinking their strategies (especially in terms of better targeting).

In table 5, the difference of global final opinion between both procedures is summarised. This shows that the heterogeneity of opinion increases under the 2001 procedure and is even higher when the NGO adopts pro-GMO strategies. This result is at odd with the implicit objectives of the new directive, which is to smoothen out differences in opinions. However, it is consistent with our earlier findings: by allowing lobbies to be more active and to intervene more regularly, the 2001 procedure does allow for increasing discrepancies between public opinion.

Therefore, it can be concluded that the 2001 procedure is effective in increasing the consistency between the final decision to reject or authorize a new GM-product and the average European opinion. But that it does not succeed in reducing heterogeneity between European countries. It can therefore be concluded that the innovations of the 2001 Directive (unanimity in the vote and increased consultation of the public) work in both directions: it does improve "democracy" but at the expenses of more attentism (since the heterogeneity in public opinions reduces the chances of obtaining an unanimous decision).

Table 5. The efficiency of NGO lobbying strategies under the 1990 and the 2001 procedures. Row 1 shows the difference in average final opinions FinOp under the 1990 vote and the 2001 vote. Row 2 shows the difference in average standard deviations of opinions SDO under the 1990 vote and the 2001 vote. Four combination are given for the strategy of NGO in both simulations: either NGOs have the same strategy in the two voting procedures, or they change strategy when the voting procedure changes. In all simulations the strategy of the firm is to campaign towards anti-GMOs countries.

	Strategy of NGO			
	Identical for both voting procedure		**Each procedure of vote is related to a different strategy**	
	Pro-GMO	**Anti-GMO**	**1990: Pro-GMO 2001: Anti-GMO**	**1990: Anti-GMO 2001: Pro-GMO**
Differences in FinOp (1990 vote minus 2001 vote)	0.45	0.21	0.75	-0.38
Differences in SDO (1990 vote – 2001 vote)	-0.25	-0.10	-0.17	-0.18

7 Conclusion

Although our model does not capture all subtleties of an international decision-making process, it is the first attempt–to our knowledge- to represent in a unified framework the interrelations between the voting process and the lobbying process. Building such a model helps to focus on the minimal structure needed to describe such a complex system of decision making, interlinking formal and informal rules which are not necessarily well stabilized yet in the case of Europe. Simulations revealed some interesting mechanisms and forced us to gather more information on the issues at stake. They helped us to clarify the indicators and criteria for assessing the performance of the voting procedures and lobbying strategies. The multi-agent simulation tool seem to be quite useful in that context to reconsider decision that have to be taken by diverging opinions and their representative. We want to carry on with a better understanding of the interlinked decision-making processes, but also try to improve our representation of the lobbying activity and its influence on the public opinion.

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Evaluation of Usability of Dial-a-Ride Systems by Social Simulation

Itsuki Noda[1,2], Masayuki Ohta[1], Kosuke Shinoda[1,2], Yoichiro Kumada[1,2], and Hideyuki Nakashima[1,2]

[1] Cyber Assist Research Center, AIST, Japan
[2] Japan Advanced Institute of Science and Technology

Abstract. Dial-a-ride systems attract great attentions as a style of new transportation systems for urban areas. While it is reported that such systems improve usability of bus systems when applied in a small town or area, it is not obvious how and under what conditions the system are reasonable in comparison to traditional fixed-route bus systems. We conducted several computer simulations of dial-a-ride and fixed-route systems to compare usability and profitability of both systems. Simulation results indicated that: (1) Usability of the dial-a-ride system with a fixed number of buses drops very quickly when the number of demands increases. (2) When we increase the number of buses proportionally to the number of demands, the usability of the dial-a-ride system is improved more significantly than the fixed-route system. (3) When frequency of demands is sufficiently large, the dial-a-ride system offers a reasonable solution from both usability and profitability perspectives.

1 Introduction

Dial-a-ride is a system in which a passenger calls a control center of buses and states a destination; the center re-plans the route of an appropriate bus to service the request.

The dial-a-ride system is attracting attention as a new public transportation system that provides convenient transportation for disabled persons while solving traffic-jams in urban areas. However, it is applied to limited and small-scale cases for the following several reasons:

- It is difficult to handle a huge number of passengers with many buses. Generally, the problem of finding an optimal assignment of a passenger's request to a bus is a NP-hard problem.
- It is not obvious that traditional fixed-route systems can be replaced by the dial-a-ride system. Especially, it is not clear how usability of the dial-a-ride system changes when the number of passengers increases compared with fixed-route systems.

Many researchers have already attacked the first issue. Assignment of passengers' request and planning of bus routes is considered as a variation of the

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traveling-salesman problem [KdPPS,BMRS94] and the *vehicle routing problem* [BC87,SS95,BGAB83,RR97,LL01]. Various optimization techniques are used to solve the problem. [HM95] local search and tab search respectively. Simulated annealing and GA are also applied in [Sil01,Sil00] Complexity of calculation is investigated in [HKRW01].

In addition to these works, various studies have addressed the dial-a-ride problem from the following various perspectives:

– Comparison of performance under various constraints on buses:
  Many researchers [FS01,BC87,Psa83b,Psa83a,Psa80] have investigated changes in performance when the dial-a-ride system is run with various numbers of buses.
– On-line and off-line algorithms:
  Various operations research techniques are applied to solve assignment and re-routing problems under on-line and off-line conditions [GHKR99,HKR00, FS01,AKR00,GKR01].
– Relation to other traffic constraints:
  [Hor02] investigated how the dial-a-ride system interacts with other long-distance transportation systems such as trains. [HB02] evaluated the relation between efficiency of buses and town size. [HKR00,LLdP+02] took traffic conditions into account to evaluate dial-a-ride system performance.

On the other hand, few works have examine the problem from the viewpoint of the second issue above. Currently, dial-a-ride systems serve mainly disabled persons. It is difficult for the system to get enough income from passengers' fees because the number of the disabled person is limited. We should conceptualize a way for traditional fixed-route system users to use the dial-a-ride system to increase the number of passengers, For that purpose, comparison of usabilities of fixed-route and dial-a-ride systems is necessary to clarify conditions under which the dial-a-ride system will provide a better solution for social systems as a whole. This article shows results of a comparison of usability of both of fixed-route and the dial-a-ride systems through simulation of transportation in a virtual town. In the rest of the article, we formalize the problem of dial-a-ride systems in Sect. 2 and describe a detailed setup of simulations in Sect. 3. Finally, simulation results are shown and analyzed in Sect. 4.

2 Problem Domain and Formalization

2.1 Dial-a-Ride System

There are several frameworks of dial-a-ride systems according to styles of accepting *demands*[1] and policies of bus routing. Two major style variations are:

– **Reservation style:** A passenger calls and makes a demand to the bus control center a certain period ahead of the requested departure time. For example, a passenger must make a reservation one hour before riding.

[1] We refer to a passenger's request to move from one place to another as a *demand.*

– **Real-time style:** A passenger can call a demand when she wants to ride: that is, she simply calls the control center when she wants to move.

This study presumes **real-time** service because it can be applied more generally to various conditions that include the same one of the usage of the fixed-route systems.

Bus routing policy also has some variations. For example, here are two typical policies:

– **Basic-route with optional detour routes:** A bus mainly follows a basic route; it turns into predefined optional detour routes according to passengers' requests. A passenger can embark or disembark at any place along these routes.
– **Free-routing:** A bus can run on any road in a certain area. A passenger can embark or disembark any place in the area.

We focus the **free-routing** in these policies because it provides the most important service of the dial-a-ride system.

2.2 Usability and Profitability

As written in Sect. 1, the purpose of the simulation is to compare *usabilities* and *profitabilities* of dial-a-ride and fixed-route systems. Generally, the evaluation of such criteria is difficult because usabilities depend on subjective factors and profitabilities may change according to social conditions. In order to avoid these difficulties and to enable such evaluation by simulation, we simplify usabilities and profitabilities to be handled quantitatively as follows.

For *usability,* we specifically address the primary purpose of a bus system: to provide a way for a passenger to reach her destination as quickly as possible. From this point of view, *usability* can be defined as follows:

> **Usability:** average elapsed time from when a demand is told to the bus center until the demand is satisfied.

Note that we use the time when the demand is stated instead of the time when the passenger departs because we need to compare dial-a-ride and fixed-route systems in the same condition. In the case of a fixed-route system, a passenger goes to a bus-stop when she has the demand. This means that the elapsed time is measured from then. So, we use the same measure in the case of a dial-a-ride system.

In addition to it, we suppose that a passenger never changes buses. The first reason is that it is difficult to measure physical and mental costs of the transfer. People may use a slower bus route instead of a faster one when the latter one requires many transfers. This implies that we need to interpret such costs into *usability,* which is measured by time by definition. To avoid complexity, we do not consider cases in which a passenger changes buses.

Profitability is formalized as follows. Profit (or deficit) of a bus company depends on maintenance, fuel and labor costs, and fare incomes, which vary by social and economic conditions. In addition, fare-pricing causes secondary social effects by which the number of passengers changes. Therefore, it is difficult to quantify *profitability* directly . Instead, we simplify it as a balance between fare revenue and cost, where revenue and cost change in proportion to the number of passengers and buses, respectively. In other words, *profitability* is defined as follows:

Profitability: the number of demands occurring in a unit period per bus.

2.3 Virtual Town

We compose a virtual town to prepare a field for this simulation:

- Streets in the town are arranged in a grid pattern as in Kyoto and New York.
- The town shape is a square.
- All stops are at crossings.
- There are no traffic jams.
- A bus goes through, turns left or right at a crossing with the same duration.
- There are no limitations in the passenger capacity of individual buses.
- Getting on and off buses require no time.

In this virtual town, demands occur under the following conditions:

- Demands occur with constant frequency.
- Departure and destination points are decided randomly. (All positions of crossings in the town have the same probability to be departure or destination points.)
- If a passenger reaches a the destination on foot faster than riding a bus, the passenger refuses to use a bus. In this case, the time to walk is treated as the elapsed time to complete the demand.
- A passenger does not change buses.

3 Simulation Setup

3.1 Fixed-Route Systems

Usability of a fixed-route system varies according to bus-routes. It is difficult to find the optimal set of routes to cover a town theoretically because it is affected by many factors like the number of buses, average bus speed, the number of routes, the shape of the town, and so on. Therefore, we apply a genetic algorithm (GA) to find a semi-optimal set of routes.

Individual of Fixed-Route Systems. In this simulation, an individual of GA consists of a set of bus-routes. We suppose that the number of routes is fixed, and that just one bus runs on one route. Therefore, the number of buses is equal to the number of routes. There are two route types: *normal* routes and *loop* routes. On a *normal* route, a bus runs back and forth between two terminals. On a *loop* route, a bus circulates in the loop.

Evaluation of Usability. As mentioned in Sect. 2.2, usability is measured by *average time to complete a demand* (ATCD). When a passenger decides which route to use, the ATCD (T_{demand}) can be calculated as

$$\begin{aligned} T_{\mathrm{demand}} = & (L_{\mathrm{src}} + L_{\mathrm{dst}})/V_{\mathrm{walk}} \\ & + L_{\mathrm{route}}/(M_{\mathrm{bus}} \times V_{\mathrm{bus}}) \\ & + L_{\mathrm{bus}}/V_{\mathrm{bus}}, \end{aligned} \tag{1}$$

where L_{src}, L_{dst} and L_{bus} are distances between a departure-point and a embarkation stop, between a disembarkation stop and a destination-point, and between the two stops, respectively. L_{route} is the length of the whole route. V_{walk} and V_{bus} are walking speed and bus speed; M_{bus} is the number of buses per route[2]. In the equation, the first, second, and third terms of the right-hand side indicate "time of walking", "average time of waiting at bus stop", and "time of riding a bus", respectively.

Because we evaluate the best performance of an individual (a set of bus-routes), the system seeks the best route from the set of routes and determines the best combination of stops to embark and disembark for a given demand. Note that evaluation includes ATCD of the case where a passenger chooses to walk the whole journey to the destination because walking is faster than using a bus. In this case, L_{route} and L_{bus} are assumed to be zero; $L_{\mathrm{src}} + L_{\mathrm{dst}}$ is equal to the distance between the departure-point and the destination-point.

Alternation of Generations. A generation consists of 100 individuals. Each individual is evaluated by calculating average ATCD based on (1) using 50 randomly generated demands. Then, the top 10 individuals are selected and survive to the next generation. The next generation consists of 10 survivors, 70 descendants generated from the survivors (7 descendants per surviver), and 20 new randomly-generated individuals.

Individuals in the last population (and in the initial generations) are generated as follows:

1. Choose two terminal points randomly from all crossings in the town.
2. Choose a type of route from *normal* and *loop*.
3. When the route is the *normal* type, then the route connects the two terminals by a 'L'- and 'Γ'-shaped paths. When the route is the *loop* type, the route forms a rectangle whose two diagonal apexes are the two terminals.

Descendants are generated by mutation and cross-over described as follows.

Mutation: We restrict the mutation into the following four patterns to guarantee that a mutated bus route is valid route.

Pattern A (Fig. 1-A): If a route connects two adjoining crossings by a direct edge, replace the edge to a detour of three edges (and its inverse transformation).

[2] As mentioned above, M_{bus} is fixed to be 1 in this simulation.

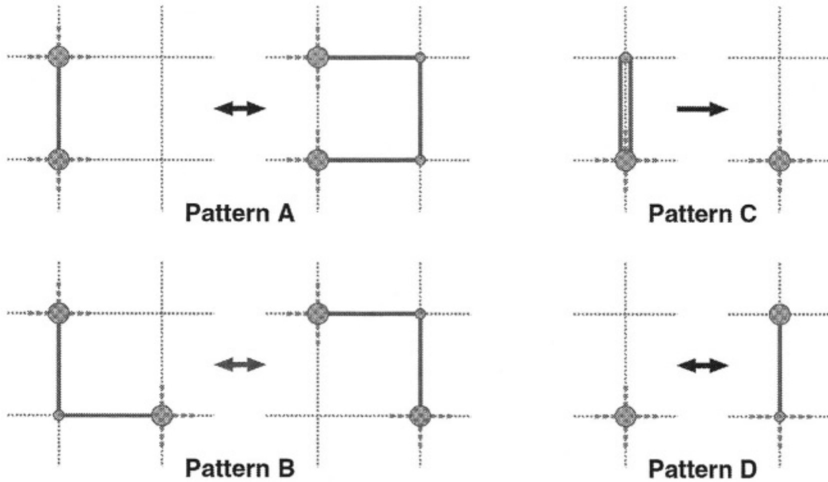


Fig. 1. Mutation pattern

- **Pattern B** (Fig. 1-B): If a route connects two diagonal crossings of a block by two edges, replace the two edges to other two edges of the block.
- **Pattern C** (Fig. 1-C): If a route has a branch that goes round between two adjoining crossings directly, shorten the branch.
- **Pattern D** (Fig. 1-D): In the case of a *normal* route, move a terminal to an adjoining crossing and extend or shorten the route.

When a descendant is generated from a parent individual, up to one mutation occurs per route.[3]

Cross-Over: Cross-over is realized by exchange routes between survivors' descendants as shown in Fig. 2. Note that the cross-over merely changes the combination of routes, not routes themselves.

Acquired Routes. Figure 3 shows examples of routes acquired by GA. These examples are the best individuals of the 10,000th generation, where the number of routes is three and the ratio of bus and walking speeds varies from 8 to 256. Figure 3 shows that the town is roughly covered by three 'L'-shape routes when bus speed is slow, while routes come to cover almost all crossings when speed increases. These results indicate that the proposed GA method can yield reasonable semi-optimal routes for a given condition.

[3] Because most mutations worsen the usability, probability to improve usability becomes very low when we apply multiple mutations per route. Therefore, we restrict the number of mutations to one per route.

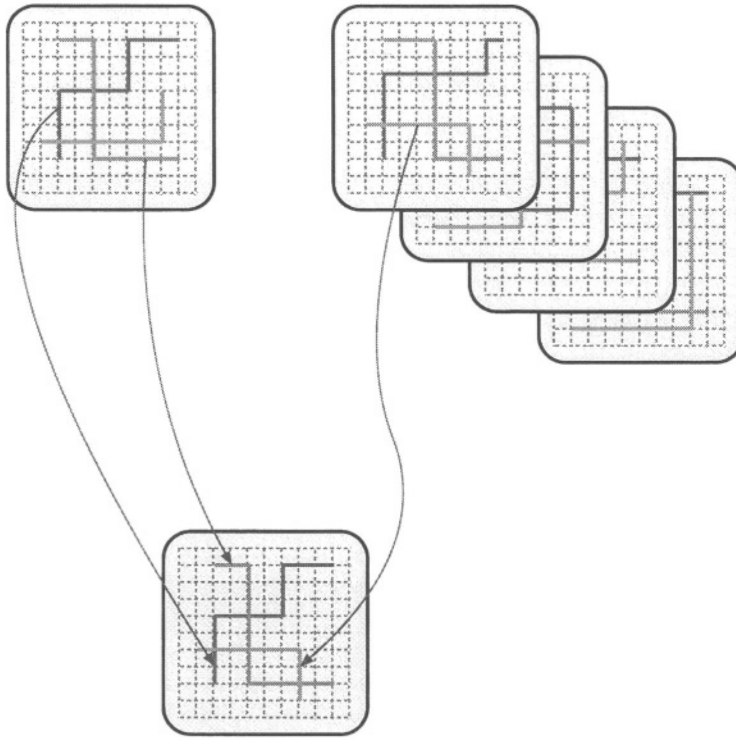


Fig. 2. Cross-over

3.2 Dial-a-Ride System

For simulation of a dial-a-ride system, we must solve problem of how to assign a new demand to buses and to re-plan a path for each bus. This is a kind of dynamic traveling salesman problem. Moreover, the problem includes more complex constraint that each demand is refused when the expected arrival time is overdue for its deadline.[4] Therefore, it is hard to find the optimal assignment in a reasonable time. Instead, we take a way to find a semi-optimal assignment by an approximation method called *successive best insertion* (Fig. 4) described as follows.

1. Each bus stores assigned demands in a via-point queue in which an assigned demand is represented by two via-points: the departure point and destination point. The bus always runs toward a via-point at the top of the queue, and removes it from the queue upon arrival. We suppose that the order of via-points in the queue is not changed after the assignment.

[4] Deadline of a demand is defined as the latest time the demand should be completed. In our simulation, the deadline is the time when the demand will be completed if the passenger walks the entire distance to the destination.

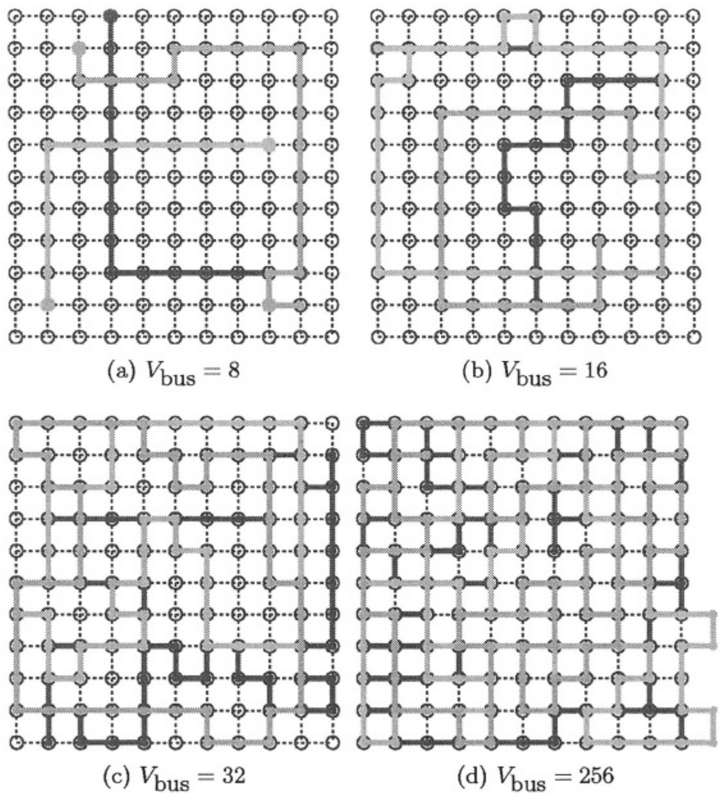


Fig. 3. Semi-optimal fixed-routes acquired by GA

2. Each bus also keeps the expected time to complete each assigned demand. The expected time is calculated by supposing that the bus will run according to the *current* queue of via-points.
3. When a new demand occurs, each bus seeks the best pair of positions to insert two via-points of demand according to the minimum of the total delay of existing demands and expected time to complete the new demand. If a deadline of existing or new demand expires by insertion, the bus reports that it has *no solution.*
4. The bus control center assigns the demand to a bus whose cost is minimum in all buses. When all buses report *no solution,* then the demand is refused.

Figure 5 shows details of the *successive best insertion* procedure.

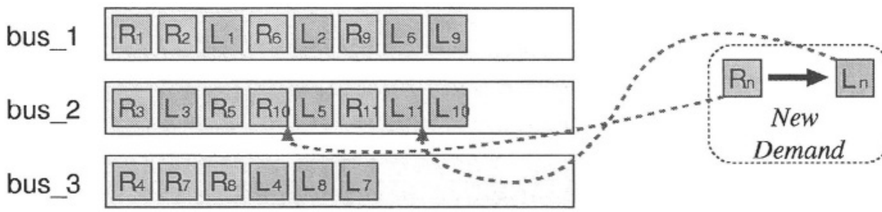


Fig. 4. Successive best insertion: When a new demand occurs, the system seeks the best pair of insertion positions for two new via-points (departure point (R) and destination point (L)) without changing existing orders in queues.

4 Simulation Result

We conducted various simulations of both bus systems using the following parameters: the size of town is 11×11, and the ratio of walking and bus speeds is $1:8$.

4.1 Case 1: Fixed Number of Buses

In the first simulation, we evaluate the case in which a fixed number of buses are used in both systems. Figure 6 shows changes of ATCD of both systems using three buses when the number of demands per unit time increases. In this figure, a strait horizontal line indicates the ATCD of the fixed-route system. The ATCD of the fixed-route system does not change according to the number of demands because we do not consider time to get on or off. On the other hand, the ATCD of the dial-a-ride system starts with small value in the case of few demands and increases immediately over the fixed-route system. This means that usability of the dial-a-ride system with the fixed number of buses degrades rapidly as the number of demands increases. The reason for change for the worse of the dial-a-ride system is that most demands are refused when many demands occur. Figure 7 shows changes of the ratio of refused demands. As indicated in this graph, the refusal ratio of the dial-a-ride system worsens more quickly than that of the fixed-route system.

4.2 Case 2: Fixed Profitability

In the second simulation, we evaluate the case when profitability of the systems is fixed. As defined in Sect. 2.2, profitability is the number of demands occurring in a unit period per bus. Therefore, in this simulation, we increase the number of buses according to the number of demands while keeping a certain ratio of demands and buses.

Figure 8 shows the simulation result. In the figure, two thick lines indicate performance of the fixed-route systems. The upper thick line is the case of a

```
proc successive-best-insertion(newDemand)
  (departPoint, destPoint) := extract(newDemand);
  bestDelay = distance(departPoint, destPoint)/walkSpeed;
  solution = noSolution;
  foreach bus ∈ busList do
    queue = getCurrentQueue;
    origDelay = calcDelayForPassenger(queue);
    foreach p ∈ queue
      insertPointBefore(departPoint, queue, p);
      foreach q ∈ subqueueAfter(queue, p);
        insertPointBefore(destPoint, queue, q);
        if (checkDeadlineForPassenger(queue))
          newDelay = calcDelayForPassenger(queue);
          delay = newDelay − origDelay;
          if (delay < bestDelay)
            bestDelay = delay;
            solution = (bus, p, q);
          fi
        fi
        removePoint(destPoint, queue);
      end
      removePoint(departPoint, queue);
    end
  end
  return solution
end
```

Fig. 5. Algorithm of successive best insertion

normal fixed-route system in which a passenger decides a route according to expected ATCD of each route. The lower thick line is the case of TIS (traffic information systems)-supported fixed-route system. This case is discussed later. Other thin lines indicate outcomes of dial-a-ride systems with various profitability. The profitability varies from $\langle \#$ of demands in unit period$\rangle / \langle \#$ of buses$\rangle =$ 1 to 16. The graph plots changes of ATCD in each case by the number of buses. This figure shows that the usabilities are improved in each case. In addition, improvement of dial-a-ride systems occurs more quickly than fixed-route systems. In both systems, the usabilities are improved because a passenger can have many choices to reach a destination. In addition, because the dial-a-ride system provides more flexibility to fit passenger's demands, the improvement is greater than with the fixed-route system.

4.3 Case 3: Comparison with TIS-Supported Fixed-Route Systems

The previous simulation presumed that a passenger decides a route according only to expected ATCD of routes in a fixed-route system. This is a reasonable

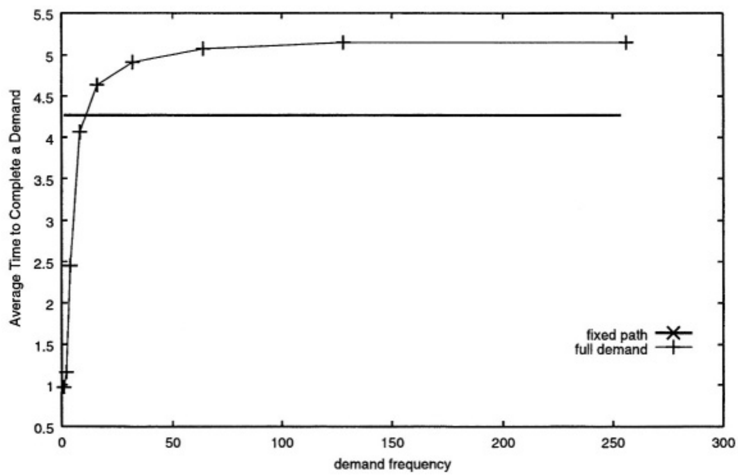


Fig. 6. Changes of average time to complete a demand in the case of three buses.

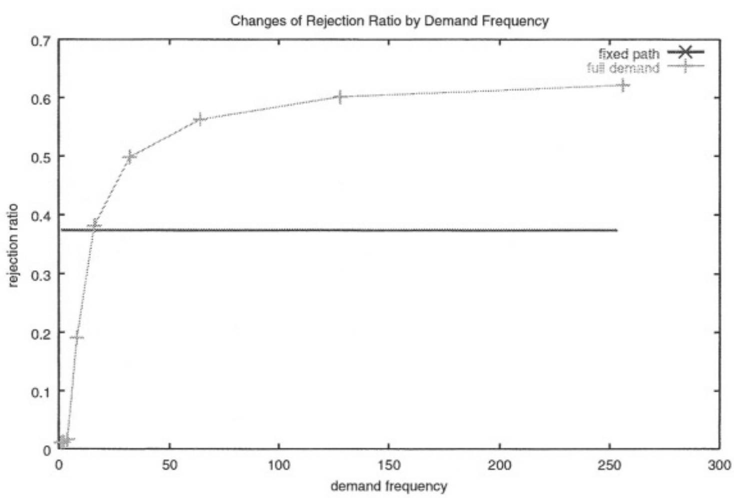


Fig. 7. Changes of ratio to refuse demands in the case of three buses.

assumption when a passenger does not know when the next bus of each route will come. However, the usability of this fixed-route system can be improved using recent TIS. Suppose that there are many possible routes that provide similar ATCD for a demand and that a passenger can know the exact time for the next bus of each route at any stop by TIS. In this case, the passenger can calculate a more accurate time to complete her demand for each route instead of the average one. Using the accurate value, she can choose a more appropriate route.

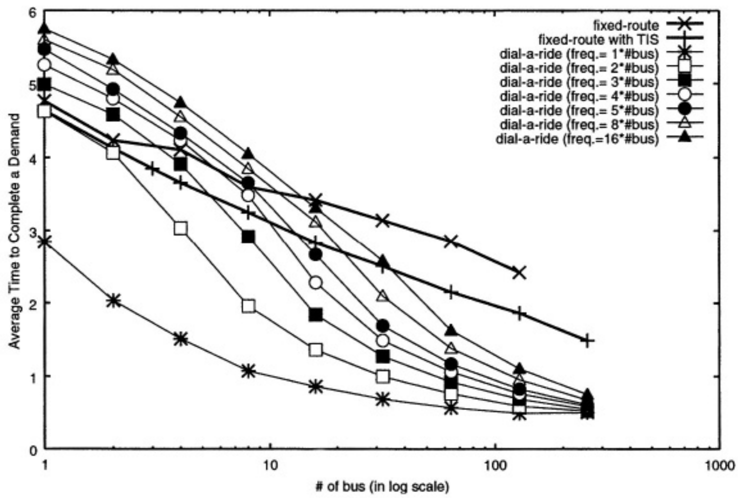


Fig. 8. Changes of average time to complete a demand when the profitability is fixed (the number of buses increases constantly according to the number of demands).

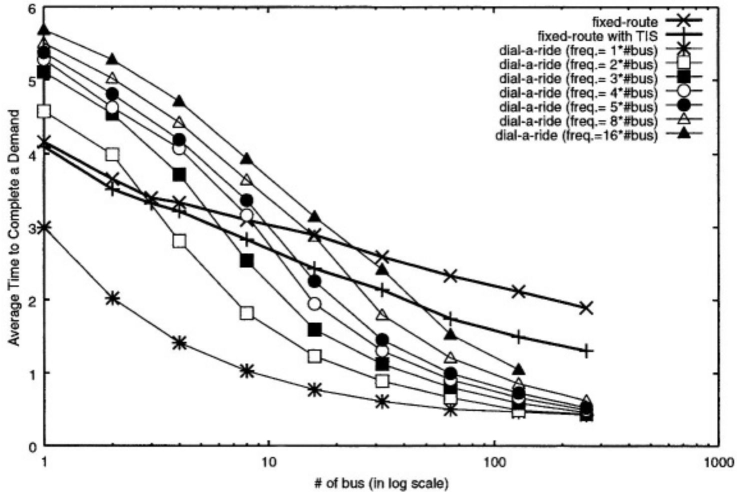
The lower thick line in Fig. 8 indicates performance of this case. As shown in the graph, usability is improved by TIS support. Improvement becomes obvious when the number of buses increases. Nevertheless, usability of the dial-a-ride system offers an advantage when the number of buses is large.

4.4 Case 4: Fixed Profitability with Converged Demands

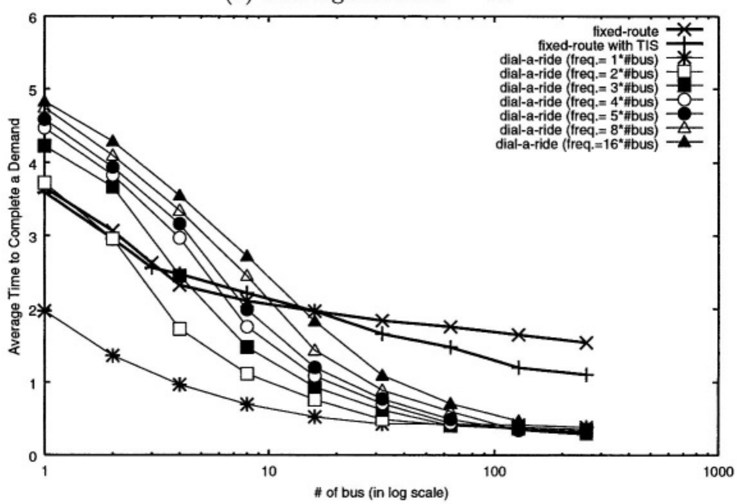
In the previous three cases, we assumed that demands occur uniformly in any place in the virtual town. However, this is not realistic because a town generally has several centers, like a train station and a shopping center, where demands converge. We conducted a simulation using converged demands to reflect such condition to the simulation.

In the simulation, we assume that there is a center of convergence of demands in the middle of the town. When a demand is generated, one departure point or destination is the center in a certain ratio, called a *convergence ratio.*

Figure 9 shows results of the simulation when the convergence ratio is (a) 0.5 and (b) 0.9. Compared these graphs and Fig. 8, we can see that the advantage of dial-a-ride systems in the usability becomes more obvious when the convergence ratio is high. For example, when a dial-a-ride system supposes that profitability ($\langle$# of demands in unit period$\rangle$/$\langle$# of buses$\rangle$) is 16, its usability becomes better than the fixed-route system with TIS at the number of buses is 64 in Fig. 8-(a) and 16 in Fig. 8-(b).



(a) convergence ratio = 0.5



(b) convergence ratio = 0.9

Fig. 9. Changes of average time to complete a demand when the profitability is fixed with converged demands.

5 Discussion and Conclusion

From results of simulations showed in the previous section, we can summarize features of a dial-a-ride system compared with a fixed-route system as follows:

- When the number of buses is fixed, the usability of the dial-a-ride system degrades quickly when the number of demands increases. On the other hand, usability of the fixed-route system is stable against changes of the number of demands until buses become full. For usability, in other words, we can choose the dial-a-ride system with a fixed number of buses only when frequency of demands is very low. This is bad news for the dial-a-ride system because it is difficult to keep usability at a reasonable level by the dial-a-ride system, while more and more demands are required for profitability. It is, therefore, not true that “dial-a-ride systems will be profitable when we have sufficient demands”.

- When the number of buses increases with the fixed profitability, usability of the dial-a-ride system is improved more quickly than the fixed-route system. Therefore, even if the case where usability of the dial-a-ride system is worse than the fixed-route system in the case of low frequent demands because of keeping the high-profitability, it gets better when the demand frequency increases.

The following open issues about the simulation remain:

- **Correspondence with real values:** Parameters in simulations shown in this article are abstracted so that it is difficult to make a correspondence with real values of actual towns. For example, we need to tune the ratio of bus and walking speeds to fit the real world and to use an actual map of a town.
- **Collaboration with other transportation system:** In actual transportation in urban area, we use several systems at the same time. Usability of a bus system should be evaluated in conjunction with other systems like trains.
- **Inconstant demands:** The simulation described here evaluates systems only under the condition where demands occur constantly. Inconstant and intermittent occurrence of demands like ’rush-hours’ are general phenomena for transportation systems. In such cases, a simulation must address a framework to switch bus systems.

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The Strategy Hypercube: Exploring Strategy Space Using Agent-Based Models

Duncan A. Robertson

Saïd Business School, University of Oxford, United Kingdom
duncan.robertson@sbs.ox.ac.uk
research@duncanrobertson.com
http://www.duncanrobertson.com/

Abstract. We demonstrate a method of representing a firm's strategy as its position and movement within an *n*-dimensional strategy space. We explore this space through the use of an agent-based model and provide preliminary results as to the appropriateness of different strategies under differing levels of environmental turbulence.

1 Introduction

Traditional management literature is based in a world that is assumed static, preferring models that assume a linear environment. Most of the models and methods available to strategists are not dynamic in nature, and have been criticized for being less than appropriate in today's turbulent, unstable environment. Such linear models may be reaching the end of their useful life for adding new insight to the strategy debate.

In order to produce a model that can cope with a dynamic environment, we first review the methods that have been used to carry out static analyses of the competitive environment. We introduce a new model that can cope with several strategic dimensions, based on but extending the strategic groups concept. We extend this methodology firstly by allowing n strategy dimensions in a strategic space that we term the 'strategy hypercube', secondly by enabling firms in our model to be truly heterogeneous rather than strictly homogeneous as in traditional industrial organization economics models, or homogeneous within heterogeneous groups as in the strategic groups paradigm. We extend the model to allow interactions not only between firms but also to 'value generating agents' that we position in the same strategy space.

We explore this strategy space using the technique of agent-based modeling, a technique that is being explored in other social science disciplines such as political science, conflict resolution, and within social systems generally, but as yet has not been fully utilized within the strategic management literature. We report preliminary observations based on simulated data from our agent-based model, in this instance applied to the banking industry, and discuss further a research agenda that can be investigated by use of this novel technique.

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2 Business Strategy

2.1 Traditional Models of Strategy

Traditional models of strategy are usually static in nature. Management scholars are used to analyzing firm strategies and classifying them into grids and matrices; however, when this form of analysis is used, little account is taken of how strategies change over time.

Hunt [12] first introduced the concept of strategic groups in his analysis of the home appliance industry; Porter [17] also used the term 'strategic groups' to represent the positioning of firms with respect to two strategic dimensions, such as the level of vertical integration and the level of specialization.

Porter [17] defines a strategic group as 'a group of firms in an industry following the same or similar strategy along the strategic dimensions'. Strategic groups analysis can take the form of a representation of firms on a two-dimensional plane whose dimensions are the strategic variables or dimensions appropriate to that particular industry.

Much of the strategic groups literature assumes that firms cluster into groups: firms are assumed to be static within the strategic groups paradigm – effort is paid to interpreting the grouping (or clustering) of firms, whereas little attention is paid to how the firms move within this strategy space (Fiegenbaum and Thomas [9]).

Authors such as Barney and Hoskisson [3] criticize the construct of using strategic groups, and propose that the assertions of strategic groups theory, firstly that strategic groups exist, and secondly that a firm's performance depends on strategic group membership, remain untested. Whilst the grouping of firms may be unproven, these authors do not criticize the validity of the construct of positioning firms in a strategy space.

Barney and Hoskisson [3] remind us that we have to consider the parent discipline of the strategic groups literature in order to place into perspective the biases that may be built in to using the strategic groups logic. Porter [17, 18] bases his research firmly in the Industrial Organization literature, where firms are considered to be homogeneous [20, 21]. Porter [16] uses the strategic group methodology in order to explain intra-industry performance differences.

Indeed, Barney and Hoskisson [3] point to the fact that, since the strategic groups concept represents a compromise between industrial organization economics 'and the traditional needs of the theory of strategy', a theory of strategy at the level of the individual firm should be developed. They point to several studies, including Barney [2] and Rumelt [20] under which firm performance depends on the idiosyncratic attributes of individual firms. The technique of agent-based modeling, described below, allows us to develop models and simulations where all firms are idiosyncratic – rather than being assumed homogeneous (as in traditional economic literature) or homogeneous with heterogeneous groups (as in strategic groups formulations). Agent-based models allow us to model an industry where firms are truly heterogeneous – and to produce results on this basis. In the past, researchers may have been limited by the lack of techniques available to study such complicated, heterogeneous systems more akin to an industrial environment experiencing high levels of turbulence.

Whilst the theoretical underpinning of strategic groups will not be used in this paper, partially on Barney and Hoskisson's [3] criticism of the technique due to its lack of robustness, the basis of using the strategic dimensions on which these firms are situated will be used. Hatten and Hatten [11]) state that '[strategic] group analysis can be used to bring key [strategic] dimensions into high relief'. We consider 'strategic space' to be a very useful conceptual tool to represent the strategy of a particular firm.

Whilst the strategic groups literature has seen the (static) position in strategy space as fully describing a firm's strategy, we shall extend this to include the way in which a firm moves in this strategy space. Indeed, we define the strategy of a firm as being the location and movement of the firm within the strategy hypercube.

2.2 Representation of Strategies

Porter's [17:131] represents firms on a two dimensional space, where firms are located on a plane at co-ordinates based upon their position with respect to two strategic dimensions, with clustering of firms indicating the strategic groups within the industry. This representation of strategic dimensions is very widely used, as it enables an easy understanding of the strategic positioning of firms and is therefore particularly successful as a didactic tool. Later research into strategic groups extended the Porter model to use multiple strategic variables. Hatten and Hatten [11] refer to the 'strategic space' resulting from multivariate analyses of strategic groups. However, a problem remains: how do we represent *n*-dimensional space? The solution may come in the mathematical device of a 'hypercube'. Whilst the positioning of firms using two strategic dimensions can be accomplished by representing the positioning on a plane, and whilst the positioning of firms using three strategic dimensions can be accomplished by representing the position of the firms within a cube, problems occur when one tries to represent firms on a space with a number of strategic dimensions exceeding three. However, higher dimensional space can be represented by using the mathematical notion of a hypercube: 'the analogue in a space of four or more dimensions of [a cube] in ordinary three-dimensional space' (*OED* [15]). We can therefore represent *n*-dimensional strategy space by using an *n*-dimensional hypercube. A representation of four-dimensional hypercube can be seen in Figure 1, below.

A firm's strategy can therefore be represented by the location and movement within the *n*-dimensional hypercube.

2.3 Exploration of Strategy Space: Agent-Based Models

Models run with the aid of computing techniques are, and have been for a long time, capable of working in higher dimensions and representing the co-ordinates of a firm in *n*-dimensional space. One advantage of using agent-based models over other computer based models is that they are capable of dealing with heterogeneous agents, or firms.

Agent-based models were partly inspired by the work of the Santa Fe Institute, who produced Swarm, a software package for multi-agent simulation of complex systems (Minar *et al.* [14]). More recently, packages such as RePast have been de veloped which are specifically designed for simulation of social science systems, and have been widely used in political science, finance, and economics (Collier [7]).

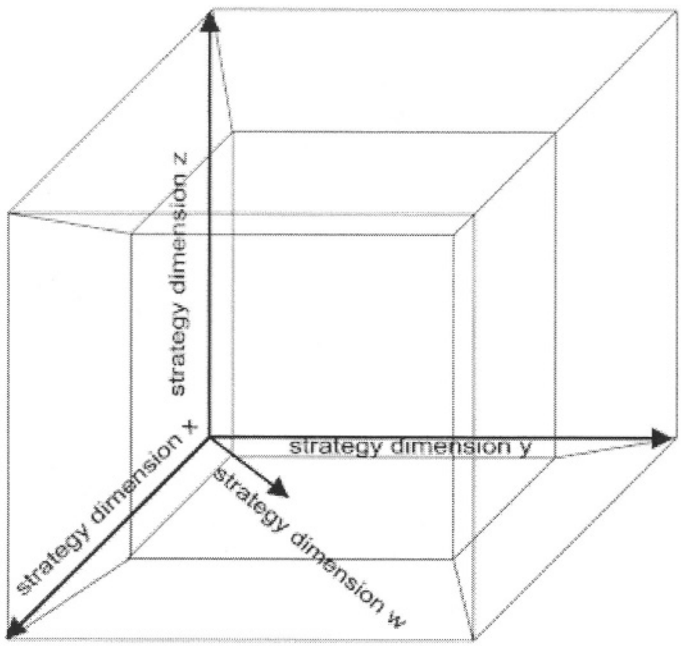

Fig. 1. Representation of a strategic hypercube having four strategic dimensions

To date, little use has been used of multi-agent simulation within strategic management. Such models do however offer an opportunity to produce simulated data that can be analyzed inductively, and aid intuition (Axelrod [1]).

The realization that the actions of one firm produce reactions within the system of firms has been widely accepted within the strategic management literature, building on the work of game theorists following von Neumann and Morgenstern [22]. However, game theoretic approaches to strategy have been criticized on the bases including the presumption that they may assume rationality of behavior (Camerer [4]). Further criticism can be leveled by the fact that game theoretical 'solutions' are usually in the form of [Nash] equilibria, and therefore are not ideally suited for a non-equilibrium system, an example of which is a turbulent industry. Agent-based models do not require equilibria to be found in order to be of use – indeed they do not require equilibrium solutions to exist. Output from the model can be used without the existence of an analytical solution, as with mainstream game theoretical solutions.

There are several advantages of using agent-based models over 'system-wide' approaches: they allow for heterogeneous agents, firms with different attributes such as profit, size, strategic location and dynamics can be modeled at the same time. Different types of agents, such as banks and customers can be modeled simultaneously. Systems can be 'open', that is agents can be created and destroyed according to the rules of the simulation; bounded rationality of agents can be incorporated: agents can be simulated whereby they have limited cognitive ability that can be different for each agent. The dynamics of the system need not be at equilibrium (a supposition of models such as those early strategy models whose roots are in neo-classical microeconomics); and emergent phenomena (such as self-organization) can be explored.

We now turn to the specific model, applied in this case to the example of the banking industry.

3 A Model for Banking Strategy

The banking industry has been described by D'Aveni [8] as one of the industries that may be considered 'hypercompetitive'. The concept of 'turbulence' has also been applied to this industry. Reger and Huff [19] identify strategic dimensions within the U.S. banking industry using a cognitive perspective. We set up an agent-based model that we intend to be used to understand strategies that may be appropriate in an industry such as this.

Firms are positioned in *n*-dimensional strategy space, and are free to move their position according to various schemata. The rate of movement of strategic position, the initial positioning, and the schema for movement can be different for each agent, thereby introducing heterogeneity amongst the firms.

We consider that competitive advantage is gained through relations with or capture of 'value generating agents' that are distributed in the same *n*-dimensional space. For the purposes of this initial simulation, to aid understanding of the model, we can simplify this assumption and assume that value-generating agents within the banking industry are customers.

The level of complexity of an agent-based model can be high, leading to a 'veridical' (Carley *et al.* [5]) model. However, we have chosen to produce a model that exhibits complex behavior whilst maintaining a high degree of parsimony. As in regression models, parsimony is favored in order to maintain ease of explanation.

Our model contains two types of agents: banks and customers. Customers are initially assumed to be fixed in strategy space. Of course, at first this may sound counterintuitive: for dynamic environments, surely we need dynamic customers? As we shall see below, a level of turbulence is created within the simulation without the need for dynamic value-generating agents. In her definition of strategic groups, Harrigan [10] states: 'strategic groups are comprised of firms who may compete for the same customers' patronage'; and thus we situate both customers and banks within the same strategic space.

One can represent the position of customers in this space as defining a 'fitness landscape' (Wright [23] [24]; Kauffman [13]) that promotes certain locations as being more preferable than others. A schematic representation of a fitness landscape can be seen in Figure 2 below.

Porter [16] defines two categories of firm – industry leaders and industry followers. Porter's definition is of leaders as being the largest firms in the industry, and followers are all other firms. In our model, we build on Porter's definition by defining the following strategies to be investigated:

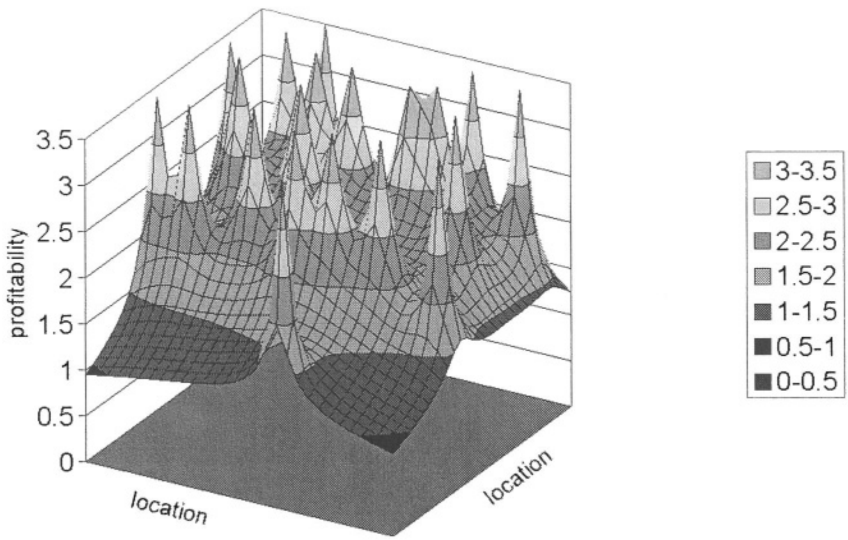

Fig. 2. Schematic Fitness Landscape produced by an inverse-square law acting on customers

- follow the leader – a firm adopting such a strategy moves their position at a constant vector within strategy space, the direction being along the line (in the *n*-dimensional hypercube) that joins the bank in question to the bank with greatest success (the lead bank). The speed of the movement can be controlled as a parameter within the model;
- do nothing – these firms do not change their position within strategy space;
- other strategies can be explored (such as withdrawing from the industry, merging with other firms, adopting a position at the 'center of mass' of the value-generating agents that are linked to the firm); these are however considered to be possible extensions to this simple model.

We further introduce a level of turbulence to the industry: by this we mean the level of stability of the value generating agents. In order to model the stability or turbulence of these agents, we allow them to travel randomly around the strategic hypercube. This is implemented by allowing the agents to take a 'random walk' where each time 'tick', the agent travels along one of the *n* dimensions, the selection of the dimension being randomly chosen, either forward or backward, through distance *T*. This allows the industry to exhibit a level of turbulence that can be varied by changing the level of *T*. Of course, if we set *T* to zero, this is the equivalent of a static environment, where all value generating agents do not move.

3.1 Methods and Resources

The RePast agent-based simulation framework, created at the University of Chicago, was used as a framework for creating the agent-based model. RePast is a software framework for creating agent-based simulations using the Java language. It provides a library of classes for creating, running, displaying and collecting data from an agent based simulation. An example of the output achieved can be seen in Figure 3, below.

3.2 Results and Analysis

1,000 runs of the model were executed, each being terminated after 1,000 'ticks' (time steps of the model). For each of these runs, the level of T (i.e. the step with which each of the customer agents took a random walk) was set at 0 (i.e. customers stable), 1, 2, 5, 10, 20, or 50. In this way, the turbulence parameter space for T was 'swept'. This resulted in 1,000 runs x 1,000 ticks x 7 levels of T, i.e. 7 million time steps or 'ticks' for the model. Results for this simulation series is shown in Figure 5 below. However, we also needed to compare the results of our simulation with the situation where all banks were stable, i.e. the test bank's strategy was to stay still (the same strategy as the other banks in the industry). A further 1,000 runs of the model were executed under the same levels of T for the same number of ticks per run, resulting in 7 million time steps. Overall, 14 million time steps were calculated for our model. At the end of each run, the profitability of the test bank was calculated, together with the profitability of the most- and the least- profitable bank within the industry. The level of the test bank's profitability was calculated as a percentage of the lead bank's profitability and plotted on a graph of percentage success (relative to the lead bank) vs. turbulence level vs. number of runs (out of 1,000) achieving this result.

The results of the simulation series where the test bank did not move – which we will term our 'control' run – are shown in Figure 4 above. This represents the strategy when the bank under question adopts a passive strategy, the only change in success coming from the change in the positioning of value-generating agents (which is analogous to the level of turbulence within the industry).

3.3 Observations

Whilst one must bear in mind the caveat that the results expressed here are from a simulated world, one can see from the results of the simulation (Figures 4 and 5) that there is a marked increase in success when a bank adopts a 'follow the leader' strategy as opposed to a 'stay still' strategy. This is to be expected, given costless movement through strategy space (see 'limitations of the model and extensions', below).

However, though one may initially think adopting a 'follow the leader' trajectory would result in a stable outcome, the model exhibited non-linear behavior. The reason for this was that, as our test bank traveled through the strategy hypercube, it passed closer to certain value generating agents and moved farther from other agents.

If one of these agents was connected to the lead bank, the change of configuration of that agent's connections may result in a change of leadership in the industry. This would mean that the test bank would then alter trajectory and move towards the new leader.

In this way, we observed cycles being set up where the change of the firm that is the leader would switch between two or more banks. This is an intriguing result in that customers need not be dynamic or turbulent in order to create a turbulent environment when observed from the bank's point of view. We call this endogenous turbulence, that is turbulence cased by the action and reaction of the firm agents that is

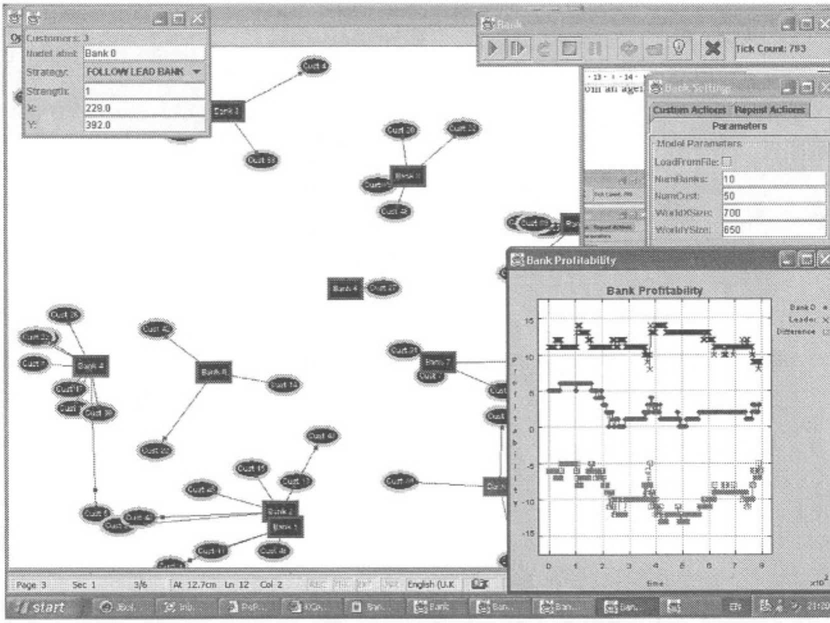

Fig. 3. Example of the output from the agent-based model

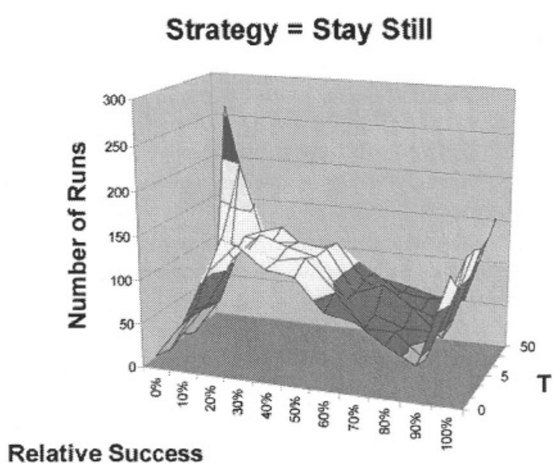

Fig. 4. Results from 1000 runs of the model where the bank's strategy is to stay still, and the level of turbulence T is 0, 1, 2, 5, 10, 20, and 50

not dependent upon there being a turbulent external environment. This is at odds with the conventional view of turbulence, where it is assumed that turbulence is caused by the external environment.

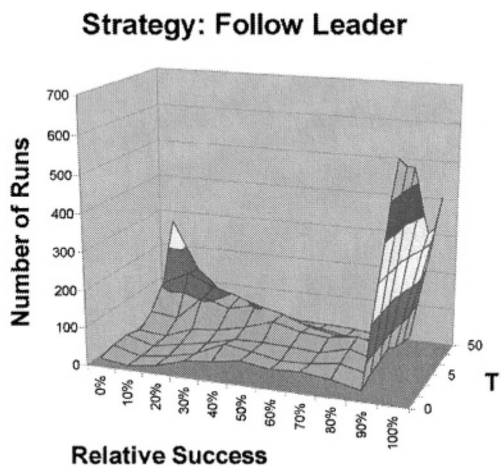

Fig. 5. Results from 1000 runs of the model where the bank's strategy is to follow the leader, and the level of turbulence T is 0, 1, 2, 5, 10, 20, and 50

3.4 Limitations of the Model and Extensions

We assume that there is no cost of moving in strategy space. This is of course a strong assumption, but one that is justified in this model on the grounds that we wish to explore the dynamics of comparing a 'follow the leader' strategy with a 'stay still' strategy. The interpretation of results becomes easier when there is only one parameter that is being swept. Were we to introduce a parameter for the cost of moving through the strategy hypercube, this would have the effect of making the interpretation of the results more difficult on the grounds that we would have to consider the interaction of the cost of moving with the strategy adopted by the test bank. We leave this as a future extension to the model.

Although the results herein describe only one simulation, one can see that this method could be extended to investigate phenomena such as: what are the results when the number of strategy dimensions is increased; what is the effect of the speed of change on the bank; what are the effects of customers moving in a correlated manner rather than taking a random walk?

3.5 Applicability of the Model to the ABSS and MAS Communities

The relevance of this paper to the agent-based social simulation ('ABSS') and multi-agent systems ('MAS') communities is that it is one output of a project – RePast – that unites both 'camps'. Software libraries such as RePast do a great deal to enable social scientists to participate in active modeling, even though a non-trivial understanding of computer languages such as Java is required. More simple interfaces as being developed in SimBuilder (as are other tools such as AScape, StarLogo, and NetLogo); this will only increase the availability of agent-based modeling to other social science researchers.

Conversely, the movement of the development of such tools from transdisciplinary institutions such as the Santa Fe Institute (original developers of Swarm, a precursor of RePast) to specific social science researchers (as in the case of University of Chicago Social Sciences Research Computing, the creators of RePast) can only help to develop tools that are relevant and therefore valuable to social science researchers, for solving problems that are pertinent in the specific literature, results of which are publishable in the literature of the specific discipline, rather than using multi-agent software tools merely as a means to an end.

This interchange of ideas, developers and users can only help to enhance the adoption of multi agent based simulation as a technique within the social sciences and within management research.

4 Conclusions

The purpose of this paper is to conceptualize a new way of looking at strategy, in terms of an n-dimensional strategy hypercube, a firm's strategy being the location and movement within this strategy space. Given the conceptual difficulties of visualizing this space, agent-based models are used to gain an insight into the strategic consequences of firms moving within this space.

Our simple model using the banking industry as an example of a turbulent environment produces some surprising, counter-intuitive results, namely the phenomena of endogenous turbulence and decreasing efficacy of having a 'follow the leader' strategy under extremely high levels of turbulence.

The joint conceptualizations of the strategy hypercube and its exploration using agent-based models opens a plethora of opportunities for strategy researchers.

The use of agent-based models is valuable in this context as it allows a problem (environmental turbulence from a firm's perspective) that has until now been too complicated to investigate satisfactorily using traditional management tools, to be investigated through a new technique. The research is driven from the premise that there is an unsolved problem in the management literature, not from the point of view that there is a novel technique that can be transplanted into a new discipline. The results do however open a fascinating and rewarding research agenda.

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A Classification of Paradigmatic Models for Agent-Based Social Simulation

Maria Bruno Marietto[1,†], Nuno David[1,2,‡], Jaime Simão Sichman[1,¥], and Helder Coelho[3]

[1] Intelligent Techniques Laboratory, University of São Paulo, Brazil
{gracas.marietto, jaime.sichman}@poli.usp.br,
http://www.lti.pcs.usp.br/{~graca, ~jaime}
[2] Department of Information Science and Technology, ISCTE/DCTI, Lisbon, Portugal
Nuno.David@iscte.pt, http://www.iscte.pt/~nmcd
[3] Department of Informatics, University of Lisbon, Portugal
hcoelho@di.fc.ul.pt, http://www.di.fc.ul.pt/~hcoelho

Abstract. Given the strong interdisciplinary character of Agent-Based Social Simulation (ABSS), and the difficulties related to ambiguous terminological and methodological assumptions, there is an increasing need to make more explicit the modelling paradigm underlying each research paper or project. In this paper we propose a classification of paradigmatic models in ABSS, which characterise different ontological assumptions and pragmatic criteria with respect to their targets. The classification is composed by different classes of models at different levels of abstraction, in a layered architecture that enables switching among levels. Each class is based on different kinds of assumptions, which possibly call for different logics of scientific research. The present proposal is interesting, since the taxonomy was well validated with researchers in the field. It is a good analytical tool to characterise or compare models according to various criteria, such as methodological, philosophical, or simply pragmatic and usability criteria.

1 Introduction

After the consolidation of the multiagent paradigm in artificial intelligence, the role of Agent-Based Social Simulation (ABSS) has been acquiring importance in a large range of scientific fields, such as the social and natural sciences. Some indicators are the profusion of conferences, workshops and journals in the area, like the series of ICMAS/AAMAS workshops on Multi-Agent-Based Simulation and the Journal of Artificial Societies and Social Simulation. In particular, the sources of analogy

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between agent-based technologies and models of actual social systems have created an intense interdisciplinary meeting and cross-fertilisation between researchers from different fields, and very often with somehow different scientific backgrounds.

If there is no doubt about the appeal of interdisciplinary research in ABSS, there is not yet a clear picture of its current organisational structure. Under a dialectical perspective, one factor that hinders a general description of ABSS is its interdisciplinary character itself, which demands a difficult interlacement of different methodologies, terminologies and points of view. Some efforts are being attempted to disambiguate methodological puzzles in ABSS. The Socionics project [20], for instance, works out the advantages of integrated relationships between Distributed Artificial Intelligence (DAI) and Sociology. Another example is the First International Workshop on Collective Robotics [10], which attempts to explore the relationships between researchers of DAI, Artificial Life and Robotics, dedicated to Collective Robotics. These and other efforts represent a difficult but necessary challenge in the discipline.

In addition, one important aspect that should deserve attention is to identify different paradigmatic models that are being currently used, and clarify its methodological roles. There are presently a considerable number of models in ABSS, which seem to be founded on different ontological assumptions, such as those based on "socio-cognitive" or "rule-based" agents. Given the strong interdisciplinary character of ABSS, and the difficulties related to various terminological and methodological assumptions, there is an increasing need to make more explicit the modelling paradigm underlying each project. The analysis of model use in ABSS can guide us at various levels:

- To disambiguate concepts and assumptions, and to help distinguish or conciliate different interdisciplinary perspectives and research goals, which in ABSS involve researchers from several scientific areas. This will possibly contribute to improve synergies or/and resolve methodological confusions or incompatibilities;
- To promote a deeper discussion of several research topics, such as the problem of observation of emergent phenomena, verification and validation of different types of models, which may possibly call for different logics of scientific research.

With the aim of helping define a more precise description of ABSS, this work puts forward a classification of models. The proposal results from ongoing activities developed in the context of the SimCog project [24]. One of the goals of this project is to assess methodological questions in the intersection of multi-agent-based simulation, computer science and the social and natural sciences[1]. To this purpose we have done the following steps. We firstly identified in the literature four types of models that seem to be based on different ontological assumptions in regard to the nature of the modelled target, as well as different kinds of formalisms that are typically used to model it. Such models are explained in section 2. Secondly, an exploratory survey based on an on-line questionnaire was designed. The questionnaire included, among other questions, a multiple-choice question that invited the

[1] Another goal of the survey was to gather information about the needs of the community with respect to a multi-agent based simulation platform for socio-cognitive agents.

respondents to choose the models that could best represent their intended use of simulation. The survey involved the contribution of one hundred and ninety six (196) researchers in ABSS[2]. Later, the survey statistical results allowed us to investigate the organisational structure of those researchers according to different combinations of models. This will be presented in section 3. Finally, we have designed a classification of models in line with such organisational structure, which we will put forward in section 4.

This classification defines a better picture of the use of models in ABSS. It can be used, for instance, as a schema to conceptualise simulation according to various philosophical foundations or methodological procedures associated with different kinds of models, such as the kind of research goals that we are after or the set of desirable technological requirements to achieve those goals. We will give an example in section 4, by characterising the models according to three dimensions: (i) abstraction level for modelling the target system, (ii) type of evidence in the validation process, and (iii) application context (social scientific, technological, etc.).

2 Types of Models in ABSS

The hypothesis that we put forward is that different research and development objectives interfere in the modelling process, since they call for different types of models specified at different levels of abstraction and based on different kinds of assumptions, which possibly call for different logics of scientific research. In order to identify relevant types of models, one can adopt various criteria. Meanwhile, it is possible to observe certain prominent patterns in the literature. We have detected four different types of models that vary in relation to different ontological assumptions and formalisms to model one or more targets. We will designate these classes of models in the following way: *Artificial Social, Socio-Cognitive, Socio-Concrete* and *Prototyping for Resolution.*

A. Artificial Social Models. The level of abstraction within this trend is often purely theoretic, where the researcher is free to abstract *a priori* any relationships of mathematical, physical, social or psychological nature. If this trend is radically adopted, with no connection at all to what we conceive actual or objective in the "real world", then there is a single empirical reference to the model put forward in the simulation: the behaviour of the simulation. The emphasis of research is therefore devoted to the verification between models: to what extent is the model interpreted according to the observed behaviour of the simulation determined by the conceptual mechanisms specified in the original model? It is more usual, however, to have these models and their outcomes confronted with meaningful traits in the real world other than the simulation itself, even if at a very suggestive level. The more meaningful the model outside the simulation is, the less it is likely to be classified as a pure artificial social model. The following models vary with respect to the level of its relationship to the real world at different levels, even if very minimally and subjectively. The Daisyworld model of an imaginary planet for which its temperature is an emergent property of growing flowers [19]; the models investigating the implications of meta-

[2] 17 respondents in Asia and Oceania; 54 in Canada and USA; 116 in Europe and Russia; and 9 in Central/South America.

belief spread [17]; or the Sugascape model [13] that attempts to model human-being behaviour through very simple rules, such as rules of sexual reproduction or cultural transmission. At any rate, the intention is not to base the model and its results on strong empirical relationships to any target system, but to establish relationships at a more or less suggestive level.

B. Socio-Scientific Models. In this type of model, researchers use the theoretic framework of social, natural and/or environmental sciences to represent social phenomena. The target systems are already known as well as those for which there is some evidence about their existence. Two main directions can be detected*: socio-cognitive* and *socio-concrete* models.

B.1. Socio-Cognitive Models. This type of model is usually founded on computational animation of logic formalisms, which represent agents and social structures according to a specific theory. The animation serves a purpose of theory consistency checking and refinement. It has been considerable influenced by the experimental tradition of Artificial Intelligence and Cognitive Science, characterised by the use of cognitive agent architectures that represent explicit knowledge, such as those based on SOAR [25]. A characteristic example is the DEPNET [4] system, based on the Theory of Dependence and Social Power [2]. The authors explore a social reasoning mechanism, where the agents can represent social dependence relations not only in accord with their goals and plans, but also with what they believe to be the other agents' goals and plans. The specification of the model is based on first-order and modal logics [23]. The use of cognitive architectures of this kind is motivated by the idea of exploring how society is implemented within the minds of its members, the exploration of the *"footprints that a multi-agent system leave not only on the behaviour of its component members, but also in their minds"* [3].

The translation of formal logic-based specifications to computational algorithms, however, seems to be a problem to scalability. In consequence, most simulations tend to relax the semantics of their original models, where the agents' internal architectures become more rudimentary, and where mental objects become segments of algorithms *"in which logistic and social information are conditions for the application of given routines"* [3]. While the theoretic role of logic-based models is certainly appealing, it does not necessarily imply the ontological conception of socio-cognitive human activity, or sociological phenomena, in terms of logic-based formalisms and reasoning. For example, in contrast with the modal logic-based specification of Dignum and Conte [5], the work of Stalles and Petta [26] simulates a cognitive model of social norms based on the functional appraisal theory of emotions. Caldas and Coelho [1], for instance, simulate the aggregated performance of various institutional and normative systems by using very simple evolutionary rules.

Notwithstanding, it should always be present that, according to the theory of computation, there is always a first-order language that can simulate any execution of a program that terminates. At any rate, it is incontestable that socio-cognitive and sociological models represent a considerable part of current work in ABSS, regardless of being specified or not with the aid of logical formalisms.

B.2. Socio-Concrete Models. This type of model should desirably represent direct observations of social and institutional concrete processes. The goal is the use of social simulation *"to describe observed social systems or aspects thereof and to capture the sometimes conflicting perceptions of the social system by stakeholders and other domain experts"* (see, for example, Moss' claim in [6]), such as the modelling of socio-economic and environmental systems. The intention is to establish substantive relationships between the simulation and the target, which typically calls for data-driven empirical research in the target.

In principle, the empirical data gathered in the target should guide the specification of the model, and should be compatible with the outcomes of the simulation as well. For instance, Hemelrijk et. al [18] report a model of female dominance in group-living primates during the period of sexual attraction, in which both the specification and the outcomes of the simulation are, to a certain extent, confronted with empirical evidence. Unfortunately, even though this confrontation is desirable, it is not always possible to close the complete circle. Most modelled systems are usually complex, difficult to specify and/or produce outcomes that are very sensitive to initial conditions. As a result, most models simplify the validation process and concentrate their validation efforts either in the specification or exclusively in the outcomes. For instance, the model of Dean et al. [9] simulate historical conditions that could in *theory* explain empirical knowledge about the patterns of extinction of the Annazi population in the U.S.A. over the period 800 to 1300 A.D. The resulting explanations are thus purely theoretic. Other alternatives have proposed a weaker form of empirical validation, suggesting the use of participatory-based simulation, whereby a set of stakeholders, such as domain experts or the system end-users, contribute to discuss and negotiate the validity of the specification and the simulation results (see e.g. the work in the context of the CORMAS project [7]).

C. Prototyping for Resolution Models. The purpose of these models is to explore and test technical or end-users' requirements for given multiagent-based computer applications. The modelling of the environment should be the most realistic as possible in order to "train" the agents in similar conditions. In some cases agents in the simulation may interact with humans or other real systems. A characteristic example is the ARCHISIM project, which aims at both simulating a realistic traffic evolution and making the behaviour of the simulated drivers credible for human-drivers placed in a driving simulator [12]. Other projects involve: train new users in a system, predict behaviours of agent-oriented software end-users' actions and construct intelligent buildings [8], or assess modelled systems to subsequent application in the real world (e.g. [21]). The modelling is thus somehow normative, insofar as the model is validated according to the end-users' approval of the simulation behaviours.

3 The SimCog Survey

The SimCog survey [24] is an exploratory statistical survey that involved the contribution of a hundred and ninety-six (196) researchers. The survey adopted a non-random selection, based on a judgment sample (see [15]). This kind of sample does not allow us to generalise the survey results to the target population, but can give us good qualitative indicators. The sample frame is a list of email addresses obtained through the following sources: articles in some of the most prestigious scientific publications in the area, key researchers and email discussion lists. Data were gathered through an on-line questionnaire with thirty-four closed questions and two open questions. Responses were received between September and December 2002.

The four types of models previously described were presented as a closed multiple-choice question, and an open question was available to allow the respondents to state other types of models. For sake of brevity, we presented in the questionnaire a short description of each type of model. Figure 1 illustrates the distribution of models among the respondents. It can be observed that the vast majority of researchers chose at least one available option, and only a minority (11.7%) did not feel represented by the four options. Moreover, among the minority of respondents that completed the open question, none of them proposed alternative models. This is an encouraging result, suggesting that the proposed types of models were significantly accepted and appropriately interpreted. These results suggest that the meaning of the models was well understood.

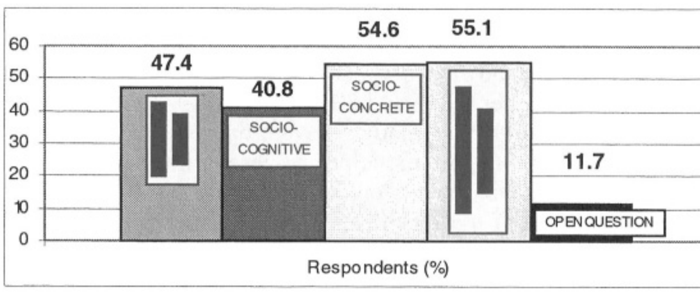

Fig. 1. Distribution of responses according to the four models.

The fact that there is a fair distribution among the four types of model does not necessarily mean that the organisation or researchers around this variable is a trivial one. Indeed, we observed a high level of spreaded choices: 28.6% of respondents chose a single option, whereas 48.5% chose two options, 13.3% chose three and 8.2% chose all options. Also, the use of artificial social models alone is negligible (<1%), since the vast majority of the respondents chose it in conjunction with other models. These results lead us to the following remarks: (i) most researchers work with more than a single type of model; (ii) socio-scientific models, including both socio-cognitive and socio-concrete approaches, seem to be more common than prototyping for resolution and artificial social models; (iii) the use of artificial social models is no more than an inspiring or complementary activity to other models. These observations are useful to hypothesise a classification of respondents according to specific sets of models, instead of just one model.

In Figure 2 we illustrate the pattern of responses organised around a tree-based classification of multiples choices, and the corresponding number of respondents for each branch and leaf. The resulting organisation was structured according to three branches, namely:

- Socio-Scientific (SS): includes respondents that chose socio-scientific models (i.e., socio-cognitive or socio-concrete), with or without the artificial social model, and did not choose prototyping for resolution;
- Prototyping for Resolution (PR): includes respondents that chose the prototyping for resolution, with or without the artificial social model, and did not choose socio-scientific models;

- Dual (D): includes respondents that chose both socio-scientific and the prototyping for resolution models, with or without the artificial social model.

All leafs are a specialisation of branches SS, PR and D. For instance, the leaf D.socio-cognitive/concrete encompasses respondents whose options were socio-cognitive *and* socio-concrete *and* prototyping for resolution models, including or not the artificial social model. Statistical results indicate that there is a significant difference between the frequencies observed in these leafs (Chi Square Goodness of Fit=58.73, DF=7, $p<0.05$).

Branch SS (85) – Researches with a Socio-Scientific approach:
SS.artificial social (3): artificial social
SS.socio-cognitive (22): socio-cognitive *or* (artificial social *and* socio-cognitive)
SS.socio-concrete (35): socio-concrete *or* (artificial social *and* socio-concrete)
SS.socio-cognitive/concrete (25): (socio-concrete *and* socio-cognitive) *or* (artificial social *and* socio-concrete *and* socio-cognitive)

Branch D (58) – Researchers with a Dual approach, including both prototyping for resolution and socio-scientific approaches:
D.socio-cognitive (11): socio-cognitive *or* (artificial social *and* socio-cognitive)
D.socio-concrete (25): socio-concrete *or* (artificial social *and* socio-concrete)
D.socio-cognitive/concrete (22): (socio-concrete *and* socio-cognitive) *or* (artificial social *and* socio-concrete *and* socio-cognitive)

Branch PR (50) – Researchers with a Prototyping for Resolution approach:
PR.prototyping-resolution (50): with *or* without artificial social

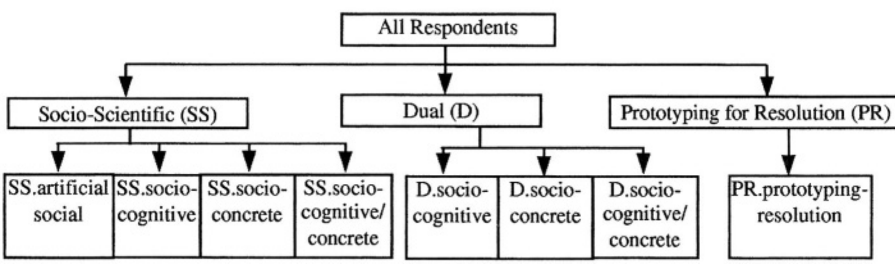

Fig. 2. Hierarchical organisation of respondents according to the four models.

4 Classification of Models

The previous results offer evidence for an overview of paradigmatic models classified according to figure 3. The classification is based on the hierarchical organisation of responses illustrated in figure 2. Table 1 associates the patterns of figure 2 with the classification in figure 3.

The classification is organised under a multi-model approach. A multi-model is a model composed by other models at several abstraction levels (see [14]). By using abstraction levels we can switch between models and use the most appropriate abstraction for a specific situation. The classification is related to other efforts to analyse the modelling process in ABSS (e.g. [11]). However, it goes a step further since: (i) it is more detailed and based on a formal framework to characterise ABSS models, (ii) it is based on a significant portion of the ABSS community.

At the top level the classification converges in the junction of two general classes: socio-analytic and techno-analytic. The meeting of socio-scientific models with the exploratory and abstract character of artificial social models converges in the class of socio-analytic models. The meeting of prototyping for resolution with artificial social models gives rise to techno-analytic models. These classes encompass general characteristics and properties. Subsequently, more specific model types are defined, associated with more specific approaches. At the top level, the meeting of socio-analytical with techno-analytic models converges in the class of socio-technical models.

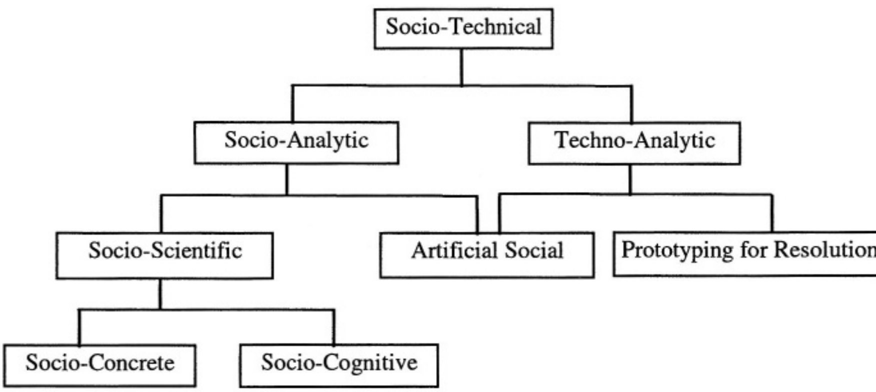

Fig. 3. Classification of models.

Table 1. Classification of models *versus* the patterns of responses in figure 2.

Classification of ABSS models	Patterns of Responses
socio-technical	branch D
socio-analytic	socio-scientific (branch SS), including or not artificial social models
techno-analytic	prototyping-resolution (branch PR), including or not artificial social models
prototyping for resolution	branch PR without artificial social models
socio-scientific	branch SS without artificial social models
socio-cognitive	leaf SS.socio-cognitive without artificial social models
socio-concrete	leaf SS.socio-concrete, without artificial social models

Socio-technical models are probably where the interdisciplinary effort between the computational sciences and the social sciences is more intense, and where agent-based theories are more often transferred between these two domains. The goal is twofold: (i) to apply theories of complex social systems to real information technologies, which should become more adaptive in response to the increasing intractability of large and decentralised software environments; (ii) to test and explore inferential consequences of those same theories, and interpret those consequences back to the social scientific domain. Examples of ongoing projects working on this basis are the Socionics [20].

4.1 Characterising the Models

One can use this classification to analyse certain features, for instance, to investigate philosophical foundations or methodological procedures for different types of models or for ABSS as a whole, as well as other practical considerations, such as the set of software requirements appropriate to certain models. After defining general requirements for top-level classes, we can walk through the multi-model and detect other relevant requirements for each specific class.

Since each modeler may have different assumptions about the world, different models can be designed based on a same target system, depending on his/her perspectives about the nature of the target or simply due to pragmatic constraints with respect to the model (e.g. computational scalability). We will use the term *dimension* to indicate any kind of perspective that may be adopted with respect to the modelling of target systems. In the rest of this paper, we will characterise the models according to three dimensions: (i) abstraction level for modelling the target system, (ii) type of evidence in the validation process, and (iii) application context.

The dimension *Abstraction Level of the Target System* (ALTS) considers that the modeller may deliberately assign different levels of hypothetical existence to the target. Three levels will be considered: *low, intermediate* and *high.* If the level of abstraction is high, then the simulated target is a pure "would be world" with no intentional relationship at all to a real world target. Conversely, if the level of abstraction is low, then there is a real intention in representing a real world target.

The dimension *Type of Evidence in the Validation Process* (TEVP) considers that the validation process seeks to assure that the specification and the simulation represent the target with an acceptable degree of adherence. We will consider two broad kinds of validation in ABSS. Validation through structural similarity, which seeks for qualitative elements of realism, striving for structural similarity between theories and the target as we know it, making it "plausible" or "credible" [16]. In addition, empirical validation considers that the main source of knowledge comes from successive experimentation, valorising perception, trial-and-error and control. We will use the following levels:

- structural-weak, when the structural similarity with the target is merely pictorial and evocative, such as the suggestive effect of colour clusters in a grid interpreted according to the real social world (e.g. the domain of ethnic segregation in the Shelling model [22]);
- structural-strong, when the structural similarity is evocated through a richer domain of descriptive representations such as mathematical-based expressions of social networks, modal-logics for mental states or organisational constraints among different actors;
- empirical-weak, when such descriptive representations are actively negotiated by stakeholders and domain experts such as in participatory-based simulations;
- empirical-strong, relying on strong empirical overt procedures and real world quantitative data.

The dimension *Application Context* (AC) considers two broad types of contexts, where simulations can be applied. The *social scientific* context, where ABSS uses the basis of social and/or natural sciences to model social phenomena; and the *technological context,* where multi-agent simulations are used to test and prototype software applications.

4.2 Investigating the Scope of ABSS

In this section we will characterise each class of models according to the three previous dimensions. By integrating all classes, we will be able to characterise the scope of ABSS in line with such dimensions. The characterisation of a subset of these classes will be our assumptions or given axioms. For purposes of illustration we will depict each class in Cartesian chart according to the aforesaid dimensions. This does not mean that the dimensions are (orthogonally) independent from each other, as we will demonstrate later on.

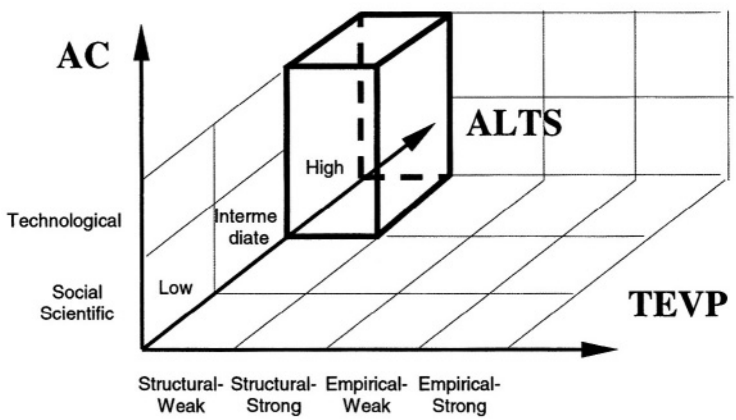

Fig. 4. Characterisation of artificial social models.

Artificial Social Models. This class involves simulations with a deliberate non-existent or weak relation to a real world target, involving simulations where:

- the application context, given by the dimension AC, can assume a technological or a social scientific context;
- the abstraction level, given by the dimension ALTS, can assume the high value;
- the validation process, defined in the dimension TEVP, can assume a structural-weak form.

Figure 4 characterises this class. For instance, in the Daisyworld model [19] we have: (i) the application context is social scientific, since it simulates the self-regulating behaviour of a population of flowers called ‘daisies’; (ii) the abstraction level is high, since the Daisyworld is an imaginary planet; (iii) the type of validation is structural-weak, because the output of the simulation is compared against an idealised structure of some hypothetical world.

Socio-Cognitive Models. Simulations in this class serve the purpose of checking the consistency or refining cognitive-based and/or sociological theories. Figure 5 characterises these models. Most of the (hypothetical) objects to which the theories refer are usually non-directly observable. The validation process is eminently qualitative and does not rely on empirical overt procedures. This class involves simulations where:

- the application context, given by the dimension AC, can assume the social scientific context;
- the abstraction level, given by the dimension ALTS, can assume the intermediate value;
- the validation process, defined in the dimension TEVP, can assume the structural-weak and structural-strong forms.

For instance, in the DEPNET model [4] we have: (i) the application context is social scientific, since the purpose of the model is to test and refine the theory of dependence and social power; (ii) the abstraction level is intermediate, since the intention is to model socio-cognitive phenomena according to a theory that is abstract and considerably analytic, not directly tied to a very specific real world situation; (iii) the validation process is structural-strong since the interpretation of the theory and the simulation results are based on a well-defined formal-logic framework, but does not rely on strong empirical overt procedures.

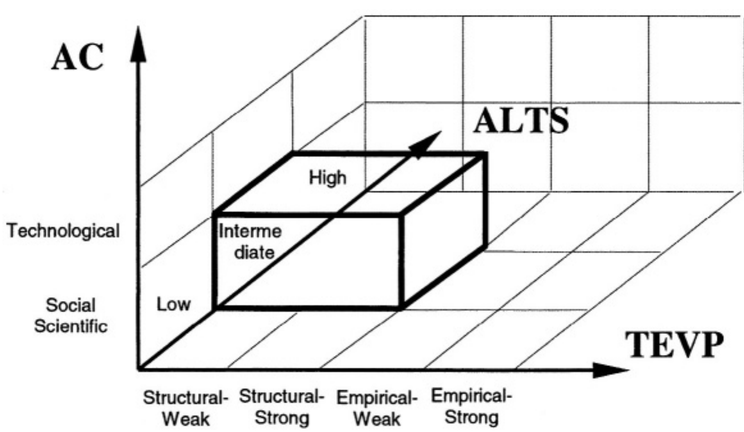

Fig. 5. Characterisation of socio-cognitive models.

Socio-Concrete Models. These models should establish substantial relationships between the simulation and the target, which typically calls for participatory based modelling and data-driven empirical research in the target. Figure 6 characterises this model. The class involves simulations where:

- the application context can assume the social scientific context;
- the abstraction level can assume the low value;

- the validation process can assume the structural-strong, empirical-weak and empirical-strong forms.

For instance, the simulation of the Kayenta Anasazi population [9] has the following characteristics: (i) the application context is social scientific, since the target of modelling is a pre-historic civilisation; (ii) the abstraction level is low, since the intention is to confront computational data with historical and archaeological aggregated data; (iii) the validation process is structural-strong, empirical-weak and empirical-strong. While the simulation outcomes are tested against empirical aggregated data and knowledge of experts, the underlying model specification is a highly hypothetical structure. In effect, this means that this model could as well be classified as a socio-analytical model (see below).

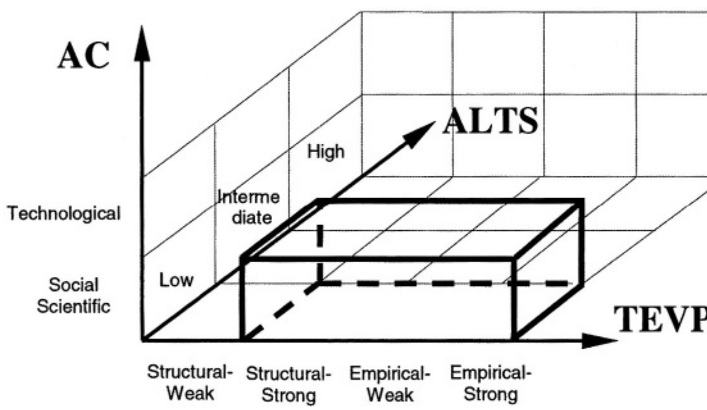

Fig. 6. Characterisation of socio-concrete models.

Socio-Scientific Models. The scope of socio-scientific models is characterised in figure 7. It is a linear integration of socio-cognitive and socio-concrete models.

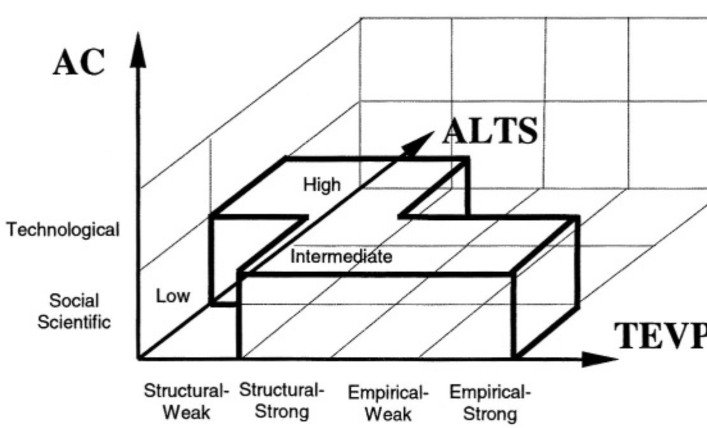

Fig. 7. Characterisation of socio-scientific models.

Socio-Analytic Models. Figure 8 characterises socio-analytic models. The class combines socio-scientific models with the exploratory character of artificial social models.

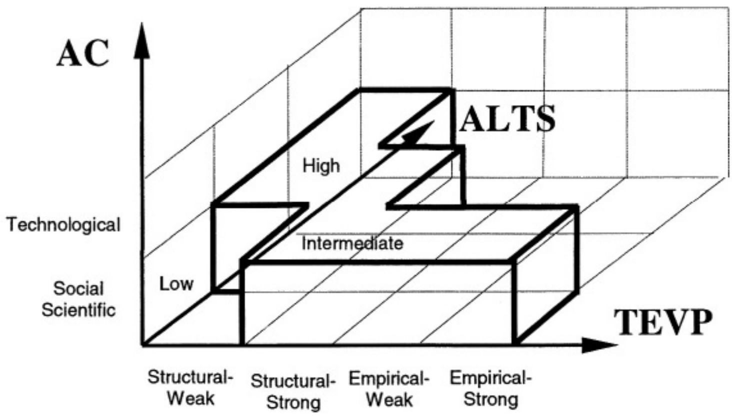

Fig. 8. Characterisation of socio-analytic models.

Prototyping for Resolution. The goal is to test intended behaviours according to technical or end-user requirements for given multi-agent systems. The validation involves tests according to technical figures (e.g. efficiency, response delay) and, quite like participatory-based modelling, the end-users' approval of the simulation behaviour. Figure 9 characterizes this model. The class involves simulations where:

- the application context can assume a technological context;
- the abstraction level can assume the low value;
- the validation process assumes the structural-strong, empirical-weak and empirical-strong forms.

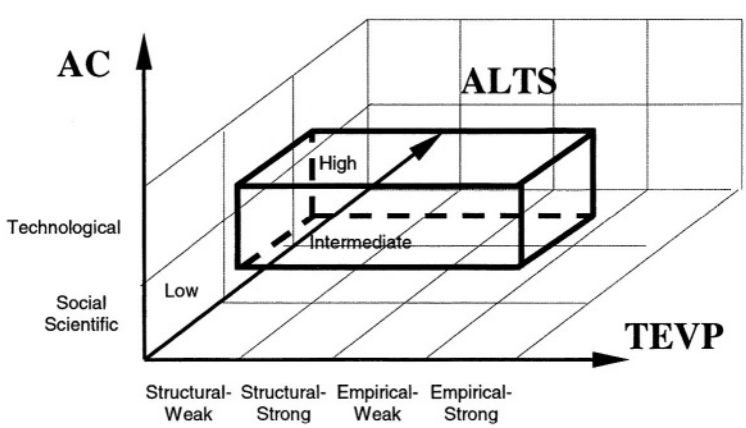

Fig. 9. Characterisation of prototyping for resolution.

For instance, the ARCHISIM [12] model, which simulates a realistic road traffic evolution, presents the following characteristics: (i) the application context is a technical one, since the ultimate goal is to make the computer behaviour credible for a human driver placed in the driving simulator; (ii) the abstraction level is low, since there is a commitment to reproduce a realistic traffic system; (iii) the validation process is empirical-weak and strong, since the output data is contrasted against real technical figures and the end-users' approvals.

Techno-Analytic. In figure 10, this class enlarges the scope of prototyping for resolution models with the exploratory influence of artificial social models. The high abstract character and structural-weak validation of artificial societies gives place to intermediate abstract levels with structural-strong validation.

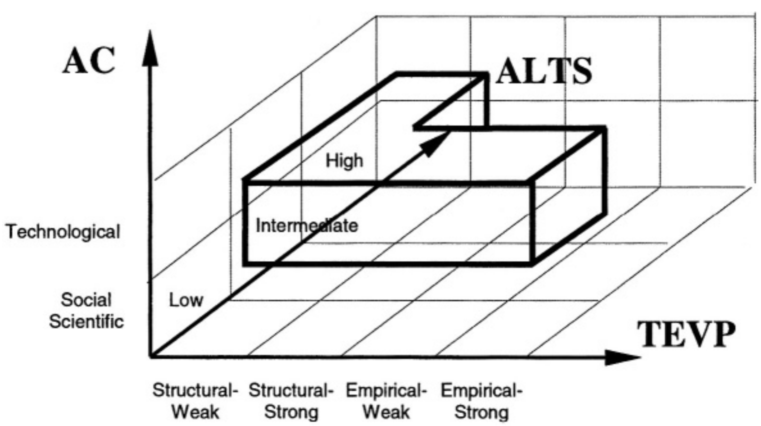

Fig. 10. Characterisation of techno-analytic models

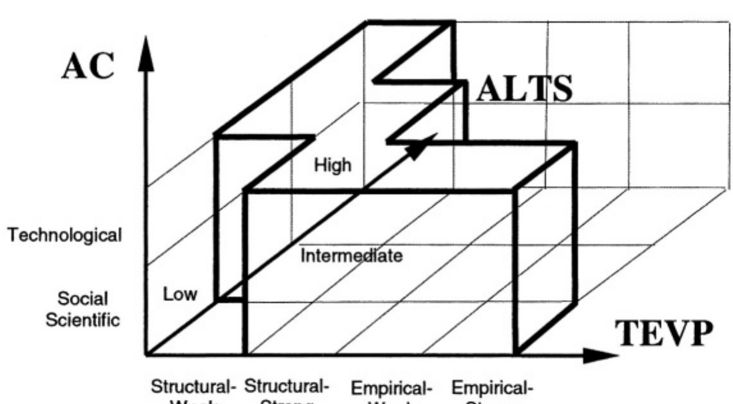

Fig. 11. Characterisation of socio-technical models.

Socio-Technical. In figure 11 we characterise simulations involving socio-technical models according to the three dimensions. These simulations should add the characteristics of prototyping with the stronger exploratory character of social analytic simulations. Socio-technical models should be the ones with the largest scope, giving us the conditions to characterise the scope of ABSS according to these three dimensions. Apparently, ABSS does *not* involve the co-ordinates:

- (structural-weak, abstraction low, {social scientific and technological contexts})
- (structural-strong, abstraction high, {social scientific and technological contexts})
- ({empirical-weak, empirical-strong}, {abstraction intermediate and high}, {social scientific and technological contexts})

Unsurprisingly, there is an incompatibility between high levels of model abstraction and strong levels of model validation. Of course, depending on the set of considered axioms, one can depict different characterisations of models, eventually by using different or additional dimensions. But although there are certainly different kinds of epistemic conceptions to validate theories, all these models are useful in their own right, provided their goals and assumptions are clearly stated.

In principle, two different simulations should only be compared if their underlying paradigmatic models and dimensions are explicitly stated. In many well-established scientific areas it is normal practice to have a specific section at the beginning of a paper describing the underlying methodological assumptions and tools. Given the strong interdisciplinary character of agent-based simulation, and the difficulties related to ambiguous terminological and methodological assumptions, there is an increasing need to make more explicit the modelling paradigm underlying each project. The present proposal is interesting, since the taxonomy was well validated with researchers in the field. It is also a useful analytical tool to assess or compare different paradigmatic models in terms of arbitrary dimensions, such as philosophical, methodological or simply pragmatic. In the future, we plan to use it in order to identify different sets of software requirements for simulation platforms, which must be consistent with its intended modelling paradigm (which in our specific case is to prototype socio-cognitive models). The set of appropriate software requirements will be investigated based on the SimCog survey statistical results.

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