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CASOS 2001

Welcome to CASOS 2001, an International Conference on Computational Social and Organizational Systems. We are pleased to welcome you to Carnegie Mellon University and Pittsburgh, PA USA.

Agenda

All talks and breaks will be held in Roberts Hall on CMU's campus. The reception and keynote dinner will be in the University Center.

CASOS 2001 – Conference			
Thursday July 5, 2001			
Time	**Location**	**Speaker**	**Title**
12:00-1:00 pm	Seagate Atrium		**Registration for Conference**
1:00-1:10 pm	Singleton	Carley & Prietula	Introduction and Welcome
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1:40-2:10 pm	Singleton	Kari Chopra & William Wallace	Experimental Evaluation of a Computational Approach to Consensus Knowledge
2:10-2:40 pm	Singleton	Jana Diesner & Eleanor T. Lewis	The Implications of Coding Techniques for Interpreting Text Analysis Results
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3:40-4:10 pm	Singleton	Isamu Okada and Toshizumi Ohta	Advantage of Human Behavioral Model using Multiagent Simulation
4:10-4:40 pm	Singleton	Matthew Cronin	A Model of Help Exchange in Business Relationships
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CASOS 2001 – Conference			
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Session 4			
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11:30-12:00 pm	Singleton	Richard Burton, Børge Obel & Michael Roach	The Lost Performance of Misfits: A Dynamic Approach to Fit and Firm Performance
12:00-12:30 pm	Singleton	Hiroshi Deguchi	Platform Externality and Lockin
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2:30-3:00 pm	Singleton	Kent Wickstrom Jensen	Designing Projects: An Evaluation of a Computational Simulation Model in the Context of small Software Desig Projects
3:00-3:30 pm	Singleton	Ashish Arora, Vidyanand Choudhary, Karthik Kannan, Ramayya Krishnan, & Rema Padman	Hierarchies Vs Markets: Using an Agent-based Marketplace
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Session 6			
4:00-4:30 pm	Singleton	Greg Adams	Beyond Control: Modeling Political Parties as Decentralized, Voluntary Organizations
4:30-5:00 pm	Singleton	Klaus Jaffe	The Economy of Altruism
5:00-5:30 pm	Singleton	"Connie" Yu Yuan	The Threshold Model of Collective Action Revisited
5:30-7:00 pm	Danforth Rm University Center		Reception
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CASOS 2001 – Conference			
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9:30-10:00 am	Singleton	David Krackhardt and Scott Feld	Leveraged Diffusion
10:00-10:30 am	Singleton	Marshall van Alstyne	Modeling Information Growth and Diffusion as a Functio of Network Structure
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4:30-5:00 pm	Singleton	Yuqing Ren, Kathleen Carley & Linda Argote	Simulating the Role of Transactive Memory in Group Training and Performance
5:00-5:30 pm	Singleton	Monique Lambert, John Kunz, Raymond Levitt	Hierarchies and Transactive Memory Systems: Crafting a Model of Flexible Exception Handling
5:30-6:00 pm	Singleton	Christina Stoica	***A model for creative ontogenesis***
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CASOS 2001 – Conference			
Sunday July 8, 2001			
Time	**Location**	**Speaker**	**Title**
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9:30-10:00 am	Singleton	Li-Chiou Chen & Kathleen Carley	A Computational Model of Computer Virus Propagation
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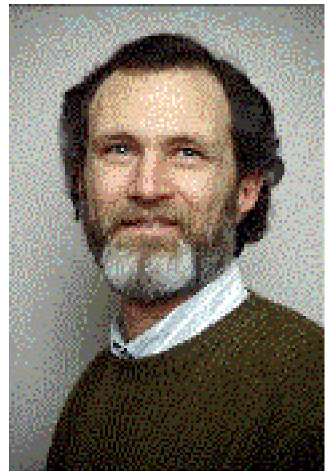
11:30-12:00 pm	Singleton	Satsuya Kurahashi & Takao Terano	Can We Control Information Free Riders? Analyzing Communal Sharing Norms via Agent-based Simulation
12:00-12:30 pm	Singleton	Hiroyuki Matsui, Isao Ono, Hiroshi Sato, Hiroshi Deguchi, Takao Terano, Hajime Kita and Yoshinori Shiozawa	Learning Economics Principles from the Bottom by both Human and Software Agents – Outline of U-Mart Project
12:30-2:00 pm	Seagate Atrium	**Lunch**	Business Meeting

Demos

Presenter	**Software**	**July 5**	**July 7**
Jana Diesner & Eleanor Lewis	Automap	Yes	Yes
Yuqing Ren & Ju-Sung Lee	Orgahead	Yes	Yes
Yuqing Ren & Alex Yahja	Construct-o	Yes	Yes
Hiroyuki Matsui & Yasuyuki Koyama	U-Mart	Yes	Yes
Marshall van Alstyne	Framework for Diffusion Models	No	Yes
Max Tsvetovat	Agent Factory	Yes	Yes
Carter Butts	Network Software	Yes	Yes
Maarten Sierhaus	Brahams	No	Yes
Klaus Jaffe	Biodynamics, Semstat, Sociodynamics	Yes	Yes
Ben Clegg	DREAMS	Yes	Yes

The Interaction Topology of Simulated Agents: New Research Lines and their Problems of Cumulation

Michael Cohen
University of Michigan



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Biography

Michael Cohen is Professor of Information and Public Policy at The University of Michigan. He has served as an External Faculty Member of the Santa Fe Institute and a long term consultant at the Xerox Palo Alto Research Center.

Cohen's research centers on processes of learning and adaptation that go on within organizations as they adjust to their changing environments. He has written numerous articles contributing to the theories of organizational decision making and learning – many employing computer simulation. The most influential of these is "A Garbage Can Model of Organizational Choice," a "citation classic" co-authored with James G. March and Johan P. Olsen. It was one of the earliest usees of what is now called "agent-based simulation" as a tool for refining theories of organizational process.

He is also the author, with Robert Axelrod, of Harnessing Complexity: Organizational Implications of a Scientific Frontier. (2000) This book aims to bring concepts derived from research on complex adaptive systems to bear on problems of management and design.

In recent years his empirical research has focused increasingly on the organizational effects of information technology. The work has involved laboratory studies as well as observation and prototype construction in field settings such as case management agencies and hospital radiology services.

He was a founding co-director of CREW, the Collaboratory for Research on Electronic Work, a multi-disciplinary research group of University of Michigan faculty. Subsequently, he joined an interdisciplinary group of faculty in creating the new School of Information that was formally chartered by the University of Michigan in 1996. He also serves as co-director of the Interdepartmental Committee on Organizational Studies (ICOS), an interdisciplinary research seminar of doctoral students and faculty that has met weekly for over a dozen years.

Interregional Relations from Spatially-Embedded Interpersonal Networks

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Past research has strongly suggested that the structure of large-scale interpersonal networks is heavily influenced by actors' positions in socio-physical space. Theorists such as Mayhew (1980; 1981; 1984) and Blau (1977) have argued for a strong role of basic socio-physical dimensions in structuring social interaction, and a long line of empirical research on such diverse relations as marriage (Bossard, 1932), college attendance (Stewart, 1941), migration and news transmission (Zipf, 1949), transportation between cities (Irwin and Hughes, 1992), friendship (Festinger et al., 1950), innovation diffusion (Hgerstrand, 1967), and memorable interaction (Latane et al., 1995) has firmly established a powerful connection between distance and interpersonal interaction. Building on this line of work, Butts and Carley (2000) proposed a formal framework for modeling the structure of large-scale interpersonal networks using an inverse distance relationship, and showed that the inverse distance model could be used to describe volumetric properties of large-scale structure. In addition, Butts and Carley demonstrated that a gravity model of inverse distance implied the existence of approximate stochastic equivalence classes defined by spatial regions, and showed that the critical radii of these regions were sufficiently large to include many human population centers. Subsequently, Butts (2000) used empirical data on tie frequency to fit a more refined power law model to the distance/tie probability relationship (ruling out a range of alternative functional forms), and found via simulation studies that the resulting models were sufficient to account for nearly all of the variability in network structure at scales of larger than approximately 1km (Butts, 2001).predictions.

Expanding on Butts and Carley (2000), the interregional relations we consider here begin with the total tie volume between regions. Let A and B be two regions in population space S. Then the interregional tie volumeV{A, B}, is given by |G[A, B}]|. We then build upon this notion to include a measure of structural influence} of A on B, which is defined by I(A}, B) = {V(A}, B)}/{V(B) + B(A}). The extent to which B is absorbed into A is given by the structural absorption, A(A,B) = { V(A, B)}/{V(B), and structural dominance, defined by D (A, B) = I (A, B) – I(A, B), measures the extent to which one region strongly (structurally) influences another without reciprocation.

By applying spatial models of interpersonal network structure derived from exis ing data sets (Butts, 2001) to populations in specified regions, provide predict ions regarding the behavior of the above measures in a variety of real-world con texts. Predictions for absorption of small communities by large ones under comparative static models are made, as well as predictions regarding diffusion between spatially proximate communities. Implications of population geometry for social cohesion are discussed, as are possible consequences of physical obstacles for socio-cultural development.

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Experimental Evaluation of a Computational Approach to Consensus Knowledge

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In studies of group cognition and group decision making, it is frequently desirable to construct some representation of the collective mental model of the group. In the classical case, the group interactively develops an explicit consensus model through a face-to-face meeting or through the use of computerized support. However, in some cases it is not possible for the group to develop a model in this fashion. In other cases, the focal point of the research is not the development of a group model itself; rather, the researcher wishes to integrate members' models in some fashion to support inferences about the group. Such situations create a need for computational, rather than interactive, methods of combining the group's mental models into a consensus model.

We have developed a computational method for constructing a consensus model from a collection of individual mental models (Chopra & Wallace, 2000). However, the question remains whether the solutions produced by the methodology are valid representations of the consensus of the group. To address this question, we performed an experiment in which consensus models produced by our methodology were subjectively evaluated by a panel of human judges. These models were also compared with a consensus model developed by the group itself, and with alternative models constructed according to simple heuristics. We first present a brief review of the methodology, followed by a description of the evaluation experiment and results.

Methodology

At the core of our methodology is the use of graphs to represent mental models. Such use is well-documented in the literature (Clemen, 1991; Cooke, 1994). Our methodology also borrows heavily from social network analysis techniques for modeling relations within groups (Wasserman & Faust, 1994). However, while social networks represent social structure within a group, the model we develop captures the cognitive structure among the members' mental models. A brief overview of the model is presented below; a more detailed discussion is presented in (Chopra & Wallace, 2000).

First consider a pair of mental models, where each model is represented as a graph. To quantify the differences between the two models, we use a graph metric function that computes distance between graphs. Thus our method is similar to several previous approaches to the comparison of mental models (Banks & Carley, 1994; Langfield-Smith & Wirth, 1992; Rush & Wallace, 1997). Four different metrics have been defined for the present research. The first is the *symmetric difference* metric, also known as the Hamming metric (Hamming, 1980). This metric, used in prior research (Banks & Carley, 1994; Langfield-Smith & Wirth, 1992; Rush & Wallace, 1997), simply counts the number of edges that differ between the two graphs. The second metric, the *indirect symmetric difference* metric, is similar to the symmetric difference except that it also counts the differences in indirect paths between vertices. Where the symmetric difference only captures differences in local structure between the two graphs, the indirect symmetric difference also measures differences in global structure. The third metric, the *dyadic difference* metric, was developed specifically for directed graphs. It counts the number of dyads that differ between two graphs, where a dyad is defined as a pair of vertices and the edge(s) or arc(s) between them (Wasserman & Faust, 1994). Its primary distinction from the symmetric difference lies in the way it handles arc reversal. Under the symmetric difference metric, reversing an arc in a graph creates a distance of two because two edges (the original arc and its opposite) are now different. However, under the dyadic difference metric, reversing an arc results in a distance of only one, since only one dyad is affected. The fourth metric is the *indirect dyadic difference* metric. This metric is analogous to the indirect symmetric difference, but based upon the dyadic difference rather than the symmetric difference.

To simultaneously model differences within groups of mental models, we introduce the metagraph, a "graph of graphs." The metagraph is itself a graph whose nodes are also graphs. The nodes of the metagraph represent mental models, and its edges represent the distances between pairs of mental models. The metagraph is analogous to a social network, where the relation between nodes represents cognitive distance rather than a social tie. Where the social network answers the question, "Who knows whom?" the metagraph answers the question, "Who thinks like whom?" To construct a metagraph for the group, one must first define the set of mental models that may be considered as possible consensus graphs; these models make up the vertex set of the metagraph. In the most general case, this would contain all possible graphs on the concepts included in the individuals' graphs. Secondly, a graph metric must be selected to define the edges of the metagraph. The structure of the metagraph will vary according to the metric; thus different graph metrics may yield different consensus models for the same group.

In order to determine a consensus graph, we build on the theme of prior research that computes a graph that is central to the group in some respect, such as a mean or median graph (Banks & Carley, 1994; Lapointe & Cucumel, 1997; Mulder, 1997; Rush & Wallace, 1997). We expand this concept to consider three different types of graph centers used commonly in social network analysis: the *center*, which minimizes the maximum distance to any member of the group; the *median*, which minimizes the average distance to the members of the group; and the *betweenness center*, which maximizes the number of member pairs between which a graph appears (Wasserman & Faust, 1994). Once the metagraph has been defined and a particular type of graph center has been selected, a consensus graph is found by searching the metagraph for those models that satisfy the selected graph center with respect to the original group.

Experiment

The objective of the experiment is to test the construct validity of the methodology; i.e., do the consensus graphs it produces actually represent the consensus of the group? In order to test this, we recruited a group of five graduate students to generate an initial set of mental models for a sample problem. The particular type of mental model targeted was the influence diagram, a model widely used in problem formulation and decision analysis (Clemen, 1991). An influence diagram is a directed acyclic graph that represents probabilistic dependence between variables. In the experiment, the group of students was presented with a description of the sample problem, and each student independently constructed an influence diagram. The group then interactively developed a consensus diagram.

The metagraph methodology was applied to the individual influence diagrams for various combinations of graph center and metric function. This produced a total of 14 different consensus models. For purposes of comparison, alternative models were also constructed according to a majority rule heuristic and a plurality rule heuristic. Under majority rule, an edge is present in the consensus graph if it is also present in a majority of the members' graphs. Under the plurality rule heuristic, a dyad is assigned a particular value in the consensus graph if it also takes on that value in a plurality of the members' graphs. For the given group of influence diagrams, majority rule yielded one additional consensus diagram and plurality rule yielded two distinct consensus diagrams. Including the consensus graph developed by the group itself results in a set of eighteen different consensus graphs for the group.

In order to determine which graphs provided the best measure of the group consensus, a paired comparison experiment was designed for the eighteen consensus graphs. A total of 124 judges were recruited from a pool of undergraduate and graduate students. Each judge was presented with the sample problem and the individual diagrams of the original group. The judge was then asked to perform a small number of pairwise comparisons between consensus graphs produced by the various methods (group interaction, metagraph methodology, majority heuristic, and plurality heuristic). For each comparison, the judge was asked to denote which graph was a better representation of the consensus of the group. The judge was also permitted to select "neither" to indicate no preference between the graphs. Because of the large number of graphs to be compared, each judge evaluated only a small number of pairs. Thus the experiment yielded unbalanced paired comparison data with ties, with a total of 4-7 comparisons per pair.

Analysis of the data is currently underway, including QAP analysis, ranking, test for overall equality, and multiple comparison tests. Preliminary results indicate that significant differences do exist among the graphs produced by various methods. The graph constructed by the original group was rated the highest among all the consensus graphs; however, several of the graphs produced by the metagraph methodology rated nearly as highly and outperformed the consensus graphs produced by the majority rule and plurality rule heuristics. The full results of the analysis will be presented.

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Using Automated Text Analysis to Study Self-Presentation Strategies

Eleanor T. Lewis, Jana Diesner, and Kathleen M. Carley

July 12, 2001

Extracting and representing the networks of ties between concepts in a set of texts creates a "map" of each text. Map analysis allows a researcher to compare the networks of ties between concepts in these texts by systematically reducing their content. The goals of this research paper are to answer both a methodological and a substantive question. First, how do the choices a researcher makes about how to generate maps using an automated text program alter the results, and how do these results compare to the results of hand-coding? Second, how can we interpret the results of map analysis to better understand the strategies authors use to manage their self-presentation, a central purpose of many texts. The texts we use are a subsample of a dataset of applications by entrepreneurs for an "Entrepreneur of the Year" award. Applicants value uniqueness in their application's *content* because it sets them apart and demonstrates their worthiness for the award, but the value placed on uniqueness in the *structure* of their accounts is not as clear. Our analysis allows us to extract four general self-presentation strategies: the prepared entrepreneur, the driven entrepreneur, the creative niche entrepreneur, and the humble entrepreneur (a single entrepreneur may employ multiple strategies).

Emergence of Market Segmentation: A Multi-Agent Model

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ABSTRACT

It has been observed in many instances that markets have a tendency to segment themselves into distinct sub-markets. This paper presents a multi-agent model that illustrates emergent market segmentation. The model illustrates the way local optimization processes result in an emergent global behavior.

1. INTRODUCTION

It has been noted that unregulated markets have a tendency to become increasingly segmented over time [2].

A market is often described in terms of competition and natural selection. Organizations or individual may fail to flourish in certain environmental circumstances because others compete with them for essential resources. As long as the resources which sustain the market are finite and market participants have unlimited capacity to expand their business, competition must ensue.

A.Howley [3] shows in his model that competition processes typically involve four components:

demand for resources exceeds supply,

selection eliminates weakest competitors competitors differentiate territorially or functionally,

yielding a division of labor in a number of market niches,

competitors within a niche become more similar as standard conditions of competition bring forth a uniform response.

In this paper, we present a multi-agent model that demonstrates the emergence of agent specialization and market segmentation in an environment populated by self-interested agents. The model is used in a set of experiments that show that local optimization behavior of profit maximization leads to an emergent global optimization of the market via decrease in transaction costs and decrease in communication link loads.

2. HYPOTHESIS

A Market Populated With Self-Interested Agents Will Organize Itself Into Specialized Sub-Markets. _ Results of this specialization will be:

- Decreased amount of communication needed to execute a transaction
- Lower average transaction cost
- Greater overall social welfare.

3. MARKET REPRESENTATION

The simulated market we used for our experiments consists of a central market clearing agent, and a number of identical trader agents. The trader agents within the market follow a Continuous Double Auction (*CDA*) protocol with periodic clearing [1]. In the CDA protocol, agents negotiate the transactions by submitting buy and sell bids to other agents. If an agree- ment is reached, the result of the transaction is reported to the auctioneer. The auctioneer collects transactions over a specified interval of time, then clears the market at the expiration of the bidding interval [4].

3.1 Utility and Self-Interest

All agents in the system are designed to be self-interested and myopic. Agents have no way to estimate other agents' pro ̄ts or the global welfare of the market, or to predict the direction that the market will take in the future. The main goal of the agent is to execute the buy and sell orders it receives from its customers. The agent utility from each transaction is:

U = TransactionP rice - ReserveP rice - TransactionCost ,

where the transaction price is the final price at the end of the negotiations and the reserve price value has been supplied by the customer. The transaction cost is represented as a function of communication that an agent has to do to complete a transaction. The agents have a clear incentive to optimize their communication patterns with the goal of bringing the number of messages required to complete a transaction to a minimum. They can do that by creating a social network of other agents. Stronger ties in this network are created to agents that are most likely to possess the goods in question and sell them at a fair price. If an agent fails to complete the transaction within the clearing period, it does not receive the positive utility, but still has to pay the communication costs. Thus, it is possible that an agent completes some of the clearing periods with a negative utility.

3.2 Agent Decision-Making

The agents in the market have to make a set of decisions to complete the transaction. The fitness of these decisions to the market situation is largely responsible for whether an agent will be successful (receive high utility) or not. In each clearing period, the agents must make the following decisions: Which of the market goods should be traded? _ Which agent should I talk to? Is the other I received good enough? The choice of goods and agents to talk to is done in a manner similar to choosing search paths in a simulated annealing search. The temperature of the search (i.e. the probability of making a random decision) is inversely proportional to the utilities that the agent derives from its trading activity.

4. VIRTUAL EXPERIMENTS WITH MARKETSIM

We have conducted a number of virtual experiments with the MarketSim simulation, confirming the original hypothesis that specialization of trading agents increases overall market welfare.

4.1 Baseline

The baseline study concerned a randomly initialized market, mostly populated with generalist agents (which were not capable of adaptation). We varied the size of the market and its initial probabilistic density (market saturation) and measured overall agent utility, network load and average transaction costs. The findings show that a generalist market is not a scalable system. We have observed that as market saturation and size go up, the transaction costs grow exponentially, thus reducing agent utility and overall welfare. The number of uncompleted transactions also goes up significantly. Mean- while, the network load puts a huge strain on the system (at times completely saturating the network with messages).

4.2 Emergence of Market Segmentation

As Hannan [2] states, "...Organizations may insure reliable performance by creating specialized units..." or retreating into market niches that allow a highly specialized organization to thrive. To simulate this process, agents were allowed to add and drop goods from their lists, based on the utility they gain from the transaction - thus allowing an agent to become as much of a generalist or specialist as the market conditions allow.

4.3 Global Patterns from Local Behavior

The emergent specialization has a profound effect on the market conditions. As agents specialize in selling one particular item, the network load decreases dramatically. As a consequence of a lower network load the transaction cost also decreases, which allows agents go get higher per-transaction utility. The overall market saturation also decreases, thus limiting the amount of competition in each of the market sectors and virtually eliminating any cross-talk between different sectors. This does not sound like good news for the market. However it has been noted in the literature [2] that a market shakedown often occurs after initial explosion. At the end of each shakedown the number of agents in a given market sector stabilizes at the maximum number of agents that can be sustained in the sector.

5. CONCLUSIONS

In this paper we have demonstrated a multi-agent model of a marketplace populated by self-interested adaptive agents. The model illustrates the segmentation of commodity markets by specialty - an emergent behavior borne out of local profit maximization motives. However, the local behaviors result in advancement of the global good - since the increase in segmentation of the market resulted in higher utility values, lower transaction costs and lower network loads for all agents in the market.

6. REFERENCES

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Advantage of Human Behavioral Model using Multiagent Simulation

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ABSTRACT

We propose an approach analyzing attitude fluctuations to solving localizability caused by bounded rationality for problem solving abilities in organizational coordination. So far, no search method to the global optimum in coordination problems for complex organizational systems has beed established. In the optimal theory, the simulated annealing method achieves a global optimum. In this paper, we consider the search for coordination as a fundamental principle of human behavior. This concept is applicable to an organizational simulation using a multiagent system. Therefore, the process which optimizes localizability caused by bounded rationality can be described based on human behavior. We consider these problem solving abilities are recognized to be one element of human intelligence. The approach using attitude fluctuations proposed in this paper gives insights into mechanisms such as search processes to solve coordination problems.

Keywords: bounded rationality, MAS, attitude fluctuation, coordination, simulated annealing method

1 Introduction

It is important to solve localizability caused by bounded rationality in problem solving abilities for organizational coordination. Generally, coordination is the result of a process to solve conflicts and reach a balanced working environment in working responsibilities among departments within a company hierarchy by managers. However, coordinating hierarchically may result in exceptional treatment, and the coordination cost increases when coordination is frequently achieved. Coordination can be achieved if people decide independently who tend to share value or information with. These processes can reduce managerial communication and workload so, their ability to do so is limited.

Studying of coordination behavior in social systems is an important research subject. For example, increasing popularity of the Internet increases the extent of communication between individuals. This creates many opportunities to reach consensus or create new values among large groups. Allen(1977) claims that a gate-keeper in a hub (central) position in a social network has socially the most right to being informed. Fujino(1998) points out that coordination information flow plays an important role in supply chain management by applying value chains. However, since coordination has a bounded rationality, a fully optimized orientation applying supply chain management cannot be achieved (Simon, 1986).

A search method, which determines the global optimum for coordination problems of complex organizational systems, has not been established yet. In optimal theory, a simulated annealing method obtains the global optimum. In this paper, we consider the pursuit of coordination a fundamental principle of human behavior. We can apply this concept to a simulated organization using a multiagent system. Therefore, a process, which optimizes localizability caused by bounded rationality, can be described based on patterns of human behavior. We consider these problem solving abilities are recognized to be one element of human intelligence. The attitude fluctuations approach proposed in this paper gives insights into mechanisms such as search processes to solve coordination problems.

2 Reorganizing Process

In our framework, when an agent who has a personality performs a task, the agent's personality is intrinsically involved in any decision making process. The influence of personality during task processing results in a decline in the organization's performance. We denote this as one type of organizational rigidity. The agent who recognizes the organizational rigidity reacts by improving one's performance or adapting to the environment by changing one's own attitudes.

Personality, which is usually used in psychology, has three parameters here: task stickiness, emotional interpersonal attraction, and conservatism [Okada, I. and T. Ohta, 2001].

The reorganizing process is generally said to be an organizational innovation for overcoming rigidity. However, it is necessary for the innovation to change not only the organizational structure or authority but also the inner attitudes of members belonging to the organization. Here, an attitude means the preparatory state before an action is performed. Once it recognizes that organizational rigidity exists, an agent can calculate how much reorganization, $ROrg$, is required. The amount of reorganization is the amount needed to break the rigidity causing the gap between the actual and ideal decision making. Here, the difference engine created by Minsky(1986) is defined as something that supplies the energy to change attitudes to bridge this gap.

$$D_i(ROrg) = \frac{1}{\sqrt{2\pi}\alpha ROrg} \times \exp(-\frac{(\log \alpha ROrg - 1)^2}{2}) \tag{1}$$

We define an attitude changing inequality that, given amounts of reorganization, $ROrg$, and amounts of intrinsic attitude changing, ΔPSN, judges whether or not the agent will change its attitude.

$$\frac{ROrg}{\Delta PSN} D_i(ROrg) > \beta CSV \tag{2}$$

3 Computer Simluation

Computer simulations reveal an interesting relationship that emerges between personality and organizational behaviors, in particular, the reorganizing process. We performed simulations with the model to analyze the influence of personality on the reorganizing process. For this purpose we set 10 agents and 10 tasks in 1000 simulation runs, and started the reorganizing process after 2000 simulation model times.

Above, we got some insights that personality causes organizational rigidity. In the reorganizing process the attitude changing inequality (eq.(2)) shows whether attitude changes or not. We compared three cases:

Case(1) No personality type

Case(2) Personality type showing no change in attitude

Case(3) Personality type showing change in attitude

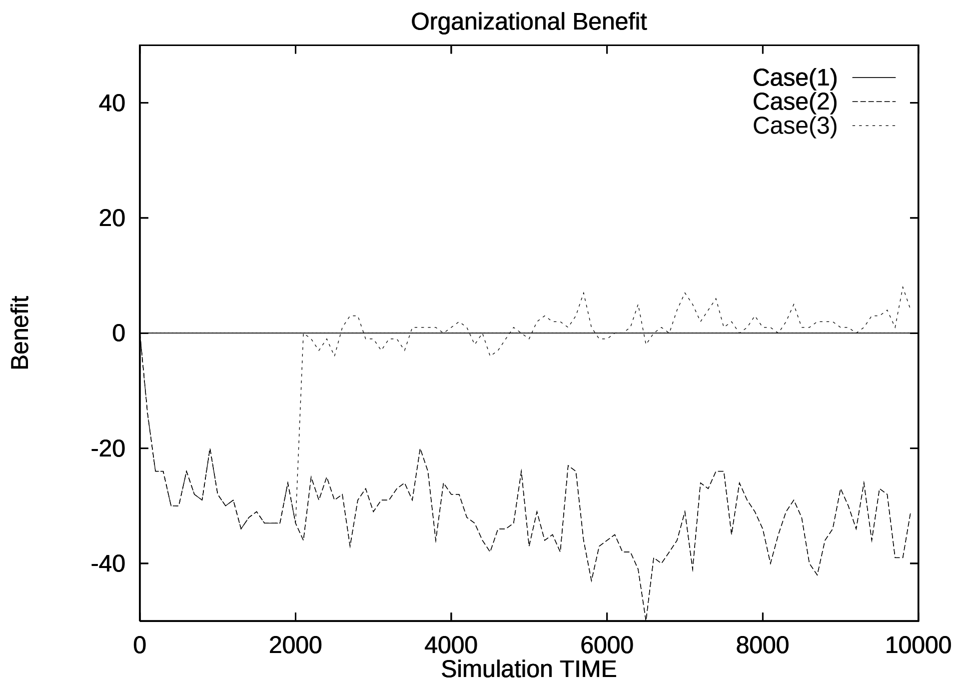

Figure 1: Organizational performance compared with the three cases

In Case(1) all agents can make the best decisions in the scope of self cognition because of bounded rationality. In Case(2) agents may not make the best decisions because personality influences the task choice function and task contact function. In Case (3) attitude change is introduced at Time=2000. Attitude change affects the task choice function and the task contract function and, in turn, the reorganizing process, as shown in figure 1.

According to figure 1, the two cases including the personality type decreased the organizational performance, but Case(3) achieved more in the reorganizing process than in Case(1). (Note: In this simulation, the attitude changing process started after 2000 model time.) This is counter intuitive. Intuition suggests that the organizational achievement in Case(1) is higher than in Case(3). A higher performance in Case (3) than in Case(1) must be counter intuitive, because Case(3) and Case (1) employ the same recognition and Case (1) employs an optimal decision function within recognition. This observation suggests that other crucial factors exist.

4 Discussion

Attitude fluctuation deceptively appears to be similar to the satisficing principle by Simon(1986). However, according to the satisficing principle, the search process stops as soon as the performance reaches a satisficing level. On the other hand, attitude fluctuation is a performance improvement process, which intentionally adapts the agent's decision makings.We consider this processes to be one of human behavior and we assume it as the global optimum for solving coorination problems for complex organizational systems.

Proper attitude fluctuations agents functioning with bounded rationality can clearly achieve effective information reorganization if agents' organizational behavioral patterns fluctuate. This mechanism suggests that personality affects reorganization because focusing on personality enables finding a method to break organizational rigidity. We propose that focusing on attitude fluctuation is important to reach a global optimum in coordination problems.

Mechanisms such as attitude fluctuation tend to emerge in a rule based multiagent simulation. According to Thomas & Seibel (2000) multiagent simulations can solve whole optimum problemsin local problem spaces by learning since they are structured comparable to an airline adaptive cargo routing system. Takahashi et. al. (2000) suggest that the bounded rationality random walk model is more cost effective than the rationality model using a multiagent simulation. We are interested that these studies use human behavior models in conjunction with a multiagent system. We consider multiagent systems applicable to describing human behavioral systems.

5 Conclusion

In this paper, we structured an organization model based on personality theory and product a concept of attitude fluctuations by using a computer simulation analysis. Our model describes a process that globalizes local optimum in the bounded rationality according to human behaviors. We consider these problem solving abilities as one element of human intelligence. Analyzing attitude fluctuation gives an insight into the global optimum in coordination problems for complex organizational systems.

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A Model of Help Exchange in Business Relationships

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This paper proposes a model of help exchange in business relationships, and tests that model using both a human experiment and a computer simulation. The theoretical foundation for this model is provided by a number of field studies on help exchange between separate businesses (e.g. Uzzi, 1996; Uzzi & Gillespie, 1998), as well as empirical research on cooperation in mixed motive games (e.g. Dawes & Orbell, 1995; Sally, 1995). These studies show that help exchange relationships have instrumental characteristics, which benefit each party, social characteristics, which link parties in ties of friendship, and a balance of obligation for the favors traded in the past. Using prior research on each of these characteristics, I develop an integrated model of giving help. I then expand the model to show how self-interested, social, and reciprocal factors influence each other as more help is exchanged. The model also includes a previously neglected aspect of help exchange: asking for help.

To test the model, I first performed an experiment where subjects played a game that simulates helping behavior between business associates. The study tests whether instrumental, social and obligatory considerations each affect giving help. It also tests how instrumental considerations affect the social and obligatory factors, as well as guide selection of whom people ask for help. Instrumental factors are shown to affect help given directly, as well as mediate obligation, liking, and whom people ask for help. I demonstrate that instrumental factors ultimately infuse the process of help exchange more thoroughly than either social or obligatory considerations.

In order to corroborate the model of helping behavior found in the human experiment, I built a computer simulation of business associates helping each other. The simulation corresponded to the human experiment, and used the findings from the human experiment to guide agent interaction. The main test of the simulation was to see if I could recover data patterns similar to subjecy's behavior in the human experiment. In addition, I tested how robust the model was to individual differences in the agents. I ran the simulation a number of times; each time I changed the parameters relating to agents initial strength of attitudes and how much random variation there was in their decision processes. The simulation corroborated the findings of the human experiment, and was very robust to random variation in individual decision processes.

The paper ultimately provides a integrated and dynamic model of helping behavior in business relationships. Additionally the paper provides a validated simulation for the model of helping behavior. I conclude that the simulation should be used to test new hypotheses about how help exchange relationships develop. In addition, the model itself should be expanded to encompass helping behavior in scenarios with more social structure than a network of independent professionals.

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Simulating Organizations using Computational and Human Agents

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This paper describes work conducted as a joint collaboration between the Virtual Design Team (VDT) research group at Stanford University (USA) and the Systems Engineering Group (SEG) at De Montfort University (UK)[2]. We describe a new docking methodology in which we combine the use of two different types of organizational simulation tool in order to comprehensively analyze complex organizational systems (projects, processes and organizational hierarchies). The VDT simulation tool operates on a standalone computer, and employs *computational agents* during simulated execution of a pre-defined process model [Kunz, 1998]. The other software tool, DREAMS[3], operates over a standard TCP/IP network, and employs *human agents* (real people) during a simulated execution of a pre-defined process model [Clegg, 2000].

We claim to have added value to DREAMS by computationally generating predictions that can be used as extra contextual knowledge by the *human agents* executing the simulation. We claim to add value to VDT by providing a simulation environment in which the *human agents* can validate, improve and make implementation plans for resolving the computationally predicted problems. Together, the tools provide a more comprehensive analysis of a work process than either type of tool can provide on its own. In this paper, we illustrate the conceptual framework for the docking methodology using a synthetic test case.

Methodology

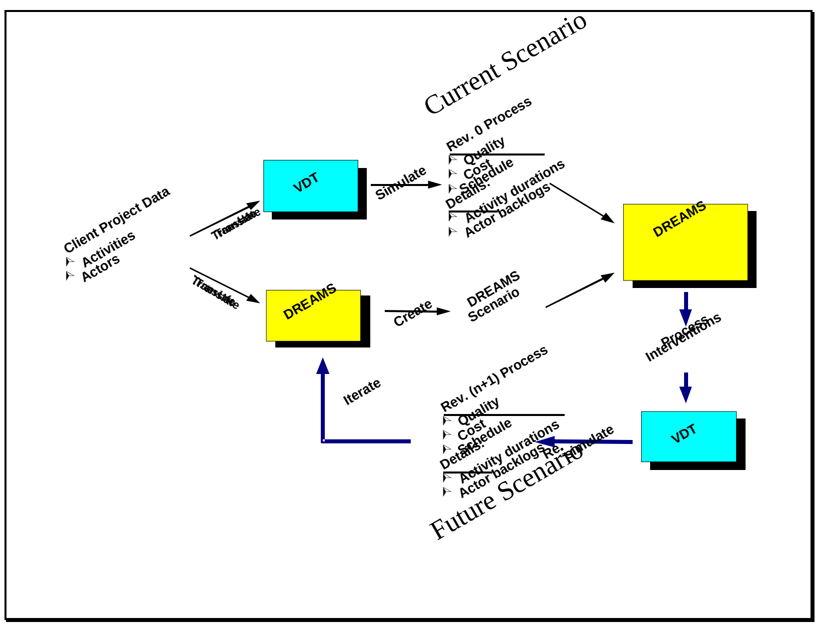

Figure 1:Docking Methodology

Figure 1 describes our overall docking methodology and shows the inputs and outputs for each tool. Both of the simulation tools use the same data set, which is used to create a model of the workflow (i.e. the process model). The process model defines the sequence of activities that comprise the workflow, as well as the specific actors that are responsible for each activity. In VDT, the output of simulation includes specific predictions regarding project schedule, process quality and human resource costs. When applied to relatively routine work processes, i.e. where details of the workflow can be explicated in sufficient detail to model, these predictions provide guidance to support managerial interventions that can be made to improve the process performance. These stochastic predictions, which are computationally generated, can give insight into how the 'real-world' organizational system behaves. They are also used to enrich the simulation experience for the *human agents* that execute a DREAMS simulation. However, a VDT simulation is inherently limited in its ability to provide useful insights into the 'real world' if demands placed on it fall outside the scope of the underlying theoretical framework that it

[2] Supported by the NSF (USA) No. IIS-9980109 and the EPSRC (UK) Nos. GRl90118 and GR/R12299/01.

[3] Dynamically Re-configurable Enterprise Agenda Management System

represents [Galbraith, 2000]. This docking methodology reflects our attempts to address this inherent limitation by using the output of a VDT simulation as a critical input to a DREAMS simulation. In contrast, DREAMS is not restricted by an underlying theoretical framework, but by the expertise of the *people* participating in the simulation.

A DREAMS simulation is executed by *human agents* (i.e. 'real people' from the 'real-world'). 'Real world' people, who hold specific tacit expert knowledge, assume the roles of *human agents.* When the matching between a persons' specific expert knowledge and the role of the *human agent* within the process model is strong, the person is said to be *'role-capable'*; together, all the participating 'role capable' people make the simulation *'role-based'*. The tool allows the 'role-capable' people to operate within a synthetic environment provided by the IP/TCP client-server architecture and execute the simulation through such functionality as an internal messaging system, a Gantt chart that has activity durations and state up-dated in *real time,* and a journal facility to record creative free thinking about process interventions. The tool is specifically designed to improve *non-routine* cross-company processes, such as competitive bidding for complex systems (e.g. a fuel pump control system for a newly developed jet engine). The tool has principally been applied to improve the practice of supply chain management [Lee, 1997] within the extended enterprise [Fine, 1998]. It requires the players to 'walk-through' the process, complete the activities, and improve the overall design and duration of the process. The DREAMS simulation allows the 'role capable' players to suggest specific solutions to resolve issues that have been predicted by VDT *as well as* suggesting additional process improvements relating to issues that are outside of VDT's theoretical representation. The DREAMS tool is best suited to developing *joint consensus about non-routine* processes.

DREAMS allows a team of 'role-capable' players to work through organizational system issues together, in a synthetic environment (this is rather like a flight crew using an aircraft flight simulator). This can even be conducted in a distributed fashion (e.g. some of the players in the UK and some of the players in the USA), and can be repeated a number of times with different players to increase the expert knowledge thrown at the solution. Thus, by combining the two simulation tools, risks predicted by VDT can be resolved specifically within a DREAMS simulation. This takes place in an environment of 'free speech' as political dimensions are reduced by the nature of role-playing. However, all player actions, such as process improvement intervention suggestions, activity duration reduction, comments to other players about how they conduct their aspects of the process, which players talk to who, about what when and why, are *all* recorded in the DREAMS database, and can be referred to during the later phases of a process improvement initiative.

The output of a DREAMS simulation, i.e., the revised (n+1) process model, is then re-simulated in the VDT model to determine if the qualitative interventions proposed by 'role-capable' players in the DREAMS simulation would result in quantitative schedule, process quality and/or cost improvements. The cycle between DREAMS and VDT is re-iterated until the whole organizational system model is improved and implementation of the results may commence.

Case Study

We illustrate the docking methodology using the synthetic test case shown in Figure 2. The test case reflects a simplified competitive bidding process, where two vendors ('Vendor A' and 'Vendor B') compete for a contract from a single 'Contract Owner' ('Actor 1'). 2 (a) shows the work process represented in VDT. 2(b) shows a portion of the work process represented in DREAMS.

It is predicted by VDT that 'Vendor B' will take twice as long (20 days) to produce a proposal than 'Vendor A' (10 days). This is based on a scenario where Vendor A has low technical skill and relevant experience, but is known to be cheap. In contrast, 'Vendor B' has high technical skill and much experience, but is expensive (these are represented in VDT in terms of 'skill level', 'application experience' and 'cost' respectively). The 'Contract Owner' has expectations that the bidding process will be completed in 40 days. However, VDT predicted the overall duration of the bidding process to take 57 days (17 days over schedule), as this includes unexpected activity dependencies and communication failures within the process. The main contribution to the absolute increased lead-time was 'Vendor B', taking an extra 8 days; an easy solution to this would be to increase the number of full time equivalents (FTEs) on this activity from 1 to 2, in other words throw more people at the problem in order to shorten the lead-time. However, a smart manager will explore other possibilities…

The competitive bid process was then simulated in DREAMS *using 'role capable' human agents instead of computational agents as responsible actors*. The players executed the same competitive bid process that had previously been simulated in the VDT model, using information regarding the schedule increase predicted by VDT. 'Role capable' players were charged with developing strategies for mitigating the predicted schedule risk. For example, a 'role capable' player (e.g. an experienced contracts manager) assuming the role of Actor 1 recommended that, "…we should abandon using Vendors A and B all together and use a new dedicated Vendor C, because neither are exactly what we are looking for, and I've used Vendor C before on another similar project in my old company; they're cheap, technically competent, and I trust them to do a good job like they did before… we could even go single source, and save manpower and cost by not needing a competitive bidding process at all! Let's develop our relationships with our supply base …". This particular process intervention requires a relatively significant modification to the original process model; i.e., the elimination of two actors and two activities, and the addition of one new actor and one new activity. Currently, recommendations such as these are given as part of a consultative process *following* VDT simulation, and the *rationale* for such recommendations are not captured. However, this proposal was *volunteered, discussed, and agreed upon* by all the other players *during* the DREAMS simulation. Therefore, there is great potential in docking these different types of simulation tool.

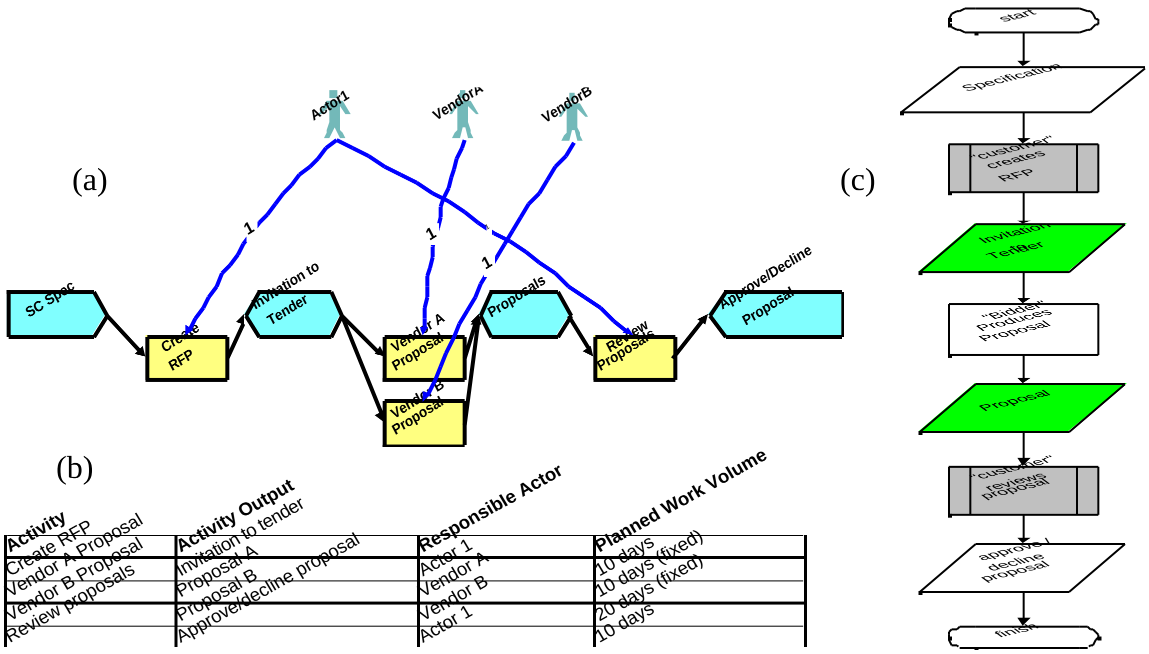

Figure 2: Test Case (a) VDT process model (b) DREAMS process model (c) activities & attributes

Summary

This docking methodology has been designed to utilize the strengths of computational and human-centered approaches to simulating organizational systems. The simple test case demonstrates that risks can be predicted about *routine* processes by simulations using stochastic modeling techniques and *computational agents*. In contrast, the test case also illustrates how people assuming roles as *human agents* and interacting through a *'role-based'* simulation environment can provide innovative, experience-based solutions to *non-routine* process problems. Together, the tools can provide more insight into a process than when either is used alone. Most importantly, the methodology can build confidence and common understanding amongst the team of users about the process and its associated problems. Such experiences are an essential and valuable pre-curser to implementing change initiatives as described above.

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Cultural and Social Evolution in Dynamic Environments

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Introduction

Optimization methods using self-adaptation mechanisms have been shown to outperform methods that do not use self-adaptation in dynamic environments [Angeline 1997]. Cultural Algorithms naturally contain self-adaptive components, which make it an ideal model to use in dynamic environments via utilizing the belief space knowledge to internally adapt to the new environment. While most evolutionary algorithms support self-adaptation at the individual component level, Cultural Algorithms support self-adaptation at both the population and the individual level.

In this paper we will discuss the explicit design and implementation of the CA components for different dynamic environments. In the next section we will discuss design and selection of the population space components. Section 3 discusses the belief space representation and design. Section 4 discuses the acceptance function design. Section 5 gives the influence function design used for different environments. Section 6 combines the CA components. Section 7 presents the results of using Morrison and DeJong's dynamic problem generator [Morrison 1999] to test the Cultural Algorithms system. The problem solving phases the emerge from the experiments are then discussed. Section 8 gives our conclusions.

Population Space Component

The population component can be represented using any population-only evolutionary computational model such as Genetic Algorithms, Evolution Strategies, Swarm, or Evolutionary Programming. Selecting one representation or another depends on the nature of the problem on hand and the types of operators needed to be preformed on the population. In general, figure 1 shows the evolution cycle of the population-only model. Since Evolutionary Programming (EP) is a model used frequently in real-valued function optimization, it will be our choice in representing the population space for this study.

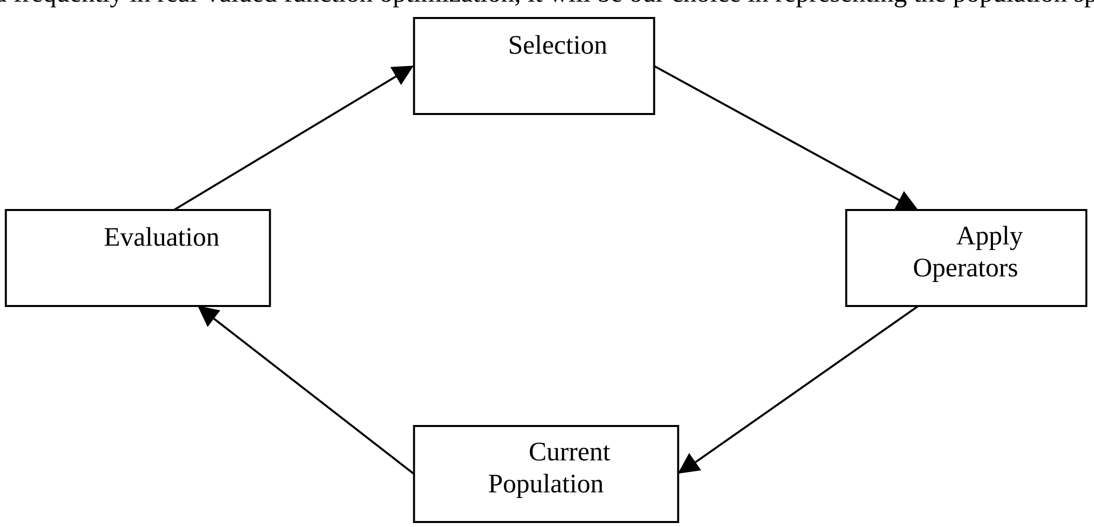


Figure 1: Evolution Cycle in Population-only Model

Belief Space Representation

Unlike the belief space representation for static environments, the belief space knowledge for dynamic environments may need more information to deal with the dynamics of change. The knowledge represented in the belief space may vary depending on the nature of the problem at hand and in the desired objectives. The belief space knowledge here consists of five major components Normative Knowledge, Situational Knowledge, Domain Knowledge, History Knowledge, and Topographical Knowledge. Normative, Topographic and Situational knowledge have been used individually in solving real-valued function optimization problems in static environments [Chung 1997] . The other two knowledge sources, History and Domain knowledge were added because of their particular use in solving dynamic problems. The Domain knowledge structure was designed to support reasoning about local dynamics whereas the History knowledge was developed to reason about global dynamics. For any given dynamic problem the belief space may actively employ some or all of the knowledge components, as shown in figure 2.

Our initial focus in this study is to identify the knowledge required by the belief space to track the optimal in dynamic environments where the functional objects being tracked are represented as a collection of peaks in a n-dimensional landscape.

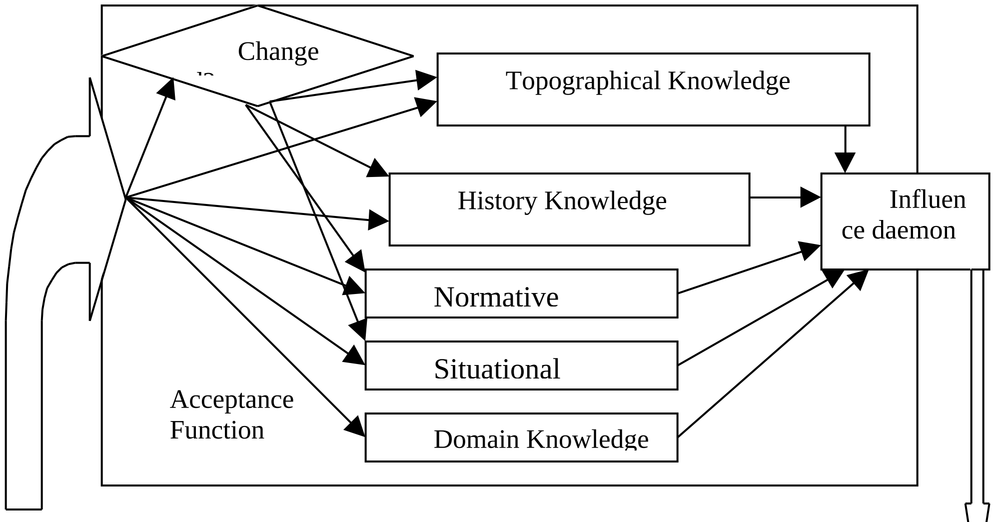
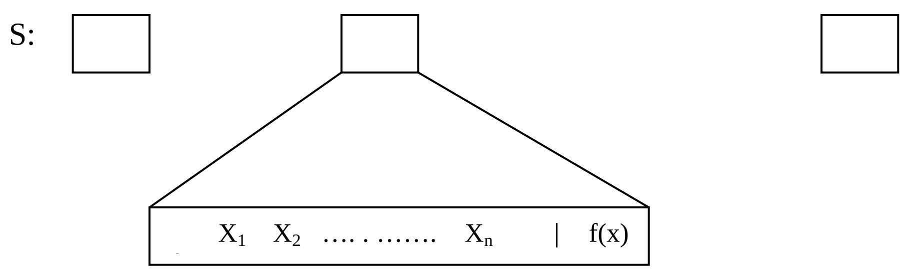


Figure 2: Belief Space Representation

The rest of this section we will discuss the representation and the update mechanism for each belief space knowledge component.

Situational Knowledge

The Situational knowledge contains a set of exemplars from the population $<e_1,\ldots,e_n>$ where n is the number of exemplars in the situational knowledge. It represents set of exemplars or examples for other individuals to follow. The data structure of the situational knowledge is represented as a list of exemplar individuals, where for each exemplar the situational knowledge contains a value for each parameter and the fitness value, as shown below:



Updating the situational knowledge simply adds the population's best individual to the situational knowledge if it outperforms the current best or it reinitializes the situational knowledge when environmental change is detected, as shown below:

$$<E_1^{t+1}, E_2^{t+1}, \ldots, E_e^{t+1}> = \begin{cases} <X_{best}^{t}, E_1^{t}, \ldots, E_{e-1}^{t}> & \text{if } f(X_{best}^{t}) > f(E_1^{t}) \\ <X_{best}^{t}> & \text{if Change Detected} \\ <E_1^{t}, E_2^{t}, \ldots, E_e^{t}> & \text{Otherwise} \end{cases},$$

where X_{best}^{t} is the best individual in the population at time t.

Domain Knowledge

The domain knowledge consists of the domain ranges for all parameters and the best examples from the population space, similar to the situational knowledge representation above. However, the purpose of this knowledge is different. For a given problem it is possible that we know something about the shape or topology of the functional landscape based upon knowledge of the problem domain. For example, here we assume that the functional landscape will be composed of many peaks or cones. Thus, changes in the landscape reflect the adjustment of these peaks. Knowledge about these conical structures can be used to make predictions about the direction and magnitude of these shifts as illustrated by figure 6. The idea there is to use changes in the fitness values from the current to the new optimum, λ , to generate diversity level and mutation step size relative to this change magnitude in the optimal solution before and after change take a place. The difference in the optimal solution, is then mapped to each variable range in order to generate mutation step sizes using the following function:

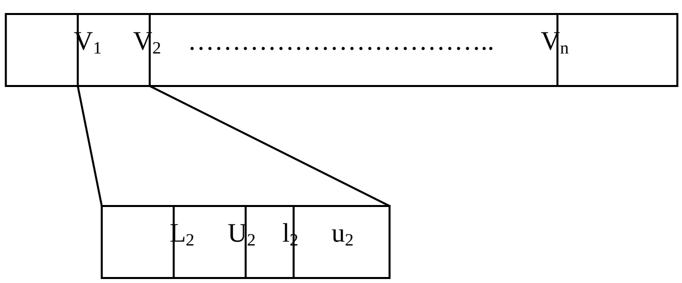
$Sh_j = \frac{r_j * \lambda}{best}$, where Sh_j is the shift size for variable j, r_j is range of variable j, and λ is the difference in the fitness value between the previous best and the best solution found so far. The update function of the domain knowledge can be given as follows:

$$\langle D_1^{t+1}, D_2^{t+1}, \ldots, D_d^{t+1} \rangle = \begin{cases} \langle x_{best}^t, D_1^t, \ldots, D_{d-1}^t \rangle & \text{if } f(x_{best}^t) > f(D_1^t) \\ \langle D_1^t, D_2^t, \ldots, D_d^t \rangle & \text{Otherwise} \end{cases}$$

, where D_1^{t+1} and D_2^{t+1} are the best and the second best exemplars in domain knowledge respectively; and x_{best}^t is current best from the population space.

Normative Knowledge

The normative knowledge is represented as a set of intervals characterizing the range of what is believed to be a good solution for each parameter [Chung 97]. These ranges provide guidelines within which individual adjustments can be made.The normative knowledge data structure for n variables is given as follows:



For each variable, V_i, the data structure contains the upper and the lower bounds l_i, u_i, and the performance value for individuals in the upper and the lower bounds, L_i, and U_i . The normative knowledge update mechanism is as follows:

Updating the lower bound for parameter j,

$$L_j^{t+1} = \begin{cases} f(x_i) & \text{if } x_{i,j} \le l_j^t \text{ or } f(x_i) < L_j^t \\ L_j^t & \text{otherwise} \end{cases}$$

$$l_j^{t+1} = \begin{cases} x_{i,j}^t & \text{if } x_{i,j}^t \le l_j^t \text{ or } f(x_i) < L_j^t \\ l_j^t & \text{otherwise} \end{cases}$$

where the i^{th} individual can affect the lower bound for parameter 'j', and l_j^t represents the lower limit for parameter 'j' at generation 't'. L_j^t denotes the performance score.

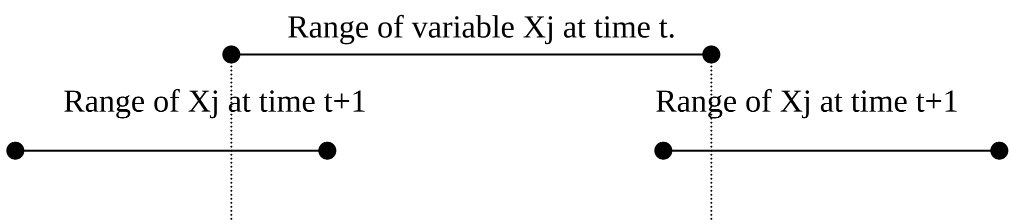
The upper bound of in parameter j is updated as follows:

$$u_j^{t+1} = \begin{cases} x_{k,j} & \text{if } x_{k,j} \ge u_j^t \text{ or } f(x_k) < U_j^t \\ u_j^t & \text{otherwise} \end{cases}$$

$$U_j^{t+1} = \begin{cases} f(x_k) & \text{if } x_{k,j} \ge u_j^t \text{ or } f(x_k) < U_j^t \\ U_j^t & \text{otherwise} \end{cases}$$

, where the K^th^ individual affects the upper bound for parameter ‘j’, and u_j^t represents the upper limit for variable j. U_j^t denotes the performance score.

Using the above update mechanism, the interval range can move toward the upper or the lower bound in real-time to track change in the environments as shown below.

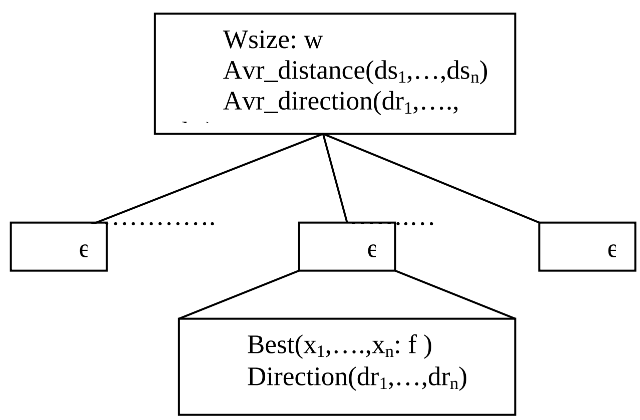


History knowledge representation and update

The history knowledge component contains information about sequences of environmental changes in terms of shifts in the distance and direction of the optimum in the search space. While the domain knowledge focused on the interpretation of a shift locally in terms of geometrical considerations, history knowledge provides a more global perspective of the change. It computes the average change in parameter values within a region, the window size, and predicts the direction of the shift in the optimum from the previous position.

The number of events stored in the history knowledge corresponds to a window size, which determines how many change events can be stored in the history list at any given time. The history knowledge contains an average shift distance and direction, and a list of change events over the sliding events window. The knowledge data structure representation can be represented as follows:

H:



where w represents the memory size for the history changing events, $(ds_1,\ldots,ds_n)$, and $(dr_1,\ldots, dr_n)$ are the average environmental changes in distance and direction respectively for each one of the n parameters. e_1 through e_w are change events. For each change event the current best solution in the previous environment and the direction of movement of each parameter relative to the current best are stored in the history list for the window, w.

When an environmental change occurs at time t, the current best solution $(x_1,\ldots,x_n: f)$ is recorded along with the directional shift $(dr_1,\ldots,dr_n)$ in the parameters of the current best and those of the best at last environment. The direction dr_j can take one of three values 1, -1 or 0 to indicate whether the parameter has increased, decreased, or remained the same. The following function is used to update the direction for parameter j of the k^th^ event:

$$e_k.dr_j = \begin{cases} 1 & \text{if } e_k.x_j - e_{k-1}.x_j > 0 \\ -1 & \text{if } e_k.x_j - e_{k-1}.x_j < 0 \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

When a new change event occurs the average size of the move is computed as shown below:

$$ds_j = \frac{\sum_{k=1}^{w-1} \left| e_k.x_j - e_{k+1}.x_j \right|}{w-1} \qquad (2)$$

,where x_j is the value of parameter j for the best solution when the change event e_k occurs and w is number of change events in the history list. The average direction of movement for the j^{th} parameter can be computed using the values calculated by (1) above, as follows.

$$dr_j = \begin{cases} 1 & \text{if } \sum_{k=1}^{w} e_k.dr_j > 0 \\ -1 & \text{if } \sum_{k=1}^{w} e_k.dr_j < 0 \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

The history knowledge is updated after every change event by updating the history list and the moving averages for each parameter as shown above in equations (2,3). The history list window is updated by adding the new change event e_i (the best solution ($x_1,\ldots,x_n$: f) and the computed directions ($dr_1,\ldots,dr_n$) as shown in equation 1) to the list. If the list has reached the maximum window size n, then the n^{th} value is dropped.

$$\langle e_1,\ldots,e_k \rangle^{t+1} = \begin{cases} \langle e_1,\ldots,e_k \rangle^{t} + e_{k+1} & \text{if } k < n \\ \langle e_2,\ldots,e_k \rangle^{t} + e_{k+1} & \text{otherwise} \end{cases}$$

, where k is the size of the current list.

Topographical knowledge

Topographical knowledge is represented in terms of a multi-dimensional grid with a cell in the grid described as $c_1,\ldots c_j$, where j is the number of dimensions and c_i is the cell size for the i^{th} dimension. The topographic knowledge structure is initialized by sampling a solution in every cell in the grid and creating a list of best n cells in the grid. It is also used to detect a change event since it samples a known value(s) in the grid in each time step. If one or more values produce a different result, a change is said to take place.

The update function divides a cell into number of smaller cells if the new fitness value of an individual is better than the fitness value of the previous best solution in that cell. If a cell is split into smaller cells, the newly generated cells are sampled and the results used to update the list of the current best n cells. For illustration, figure 3 gives an example of a two-dimensional landscape mesh where the promising cells are further divided into smaller cells.

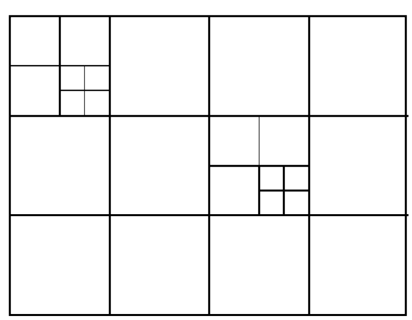


Figure 3: Landscape grid

The data structure representation is an array of size n where n is the number of cells in the mesh. Each cell in the array can produce a linked list of a new k cells when split into k smaller cells, as shown in figure 4. A cell generates children if an accepted individual's fitness value is better than the best solution in that cell, or if the fitness value of the cell's best solution has increased after a change event is detected.

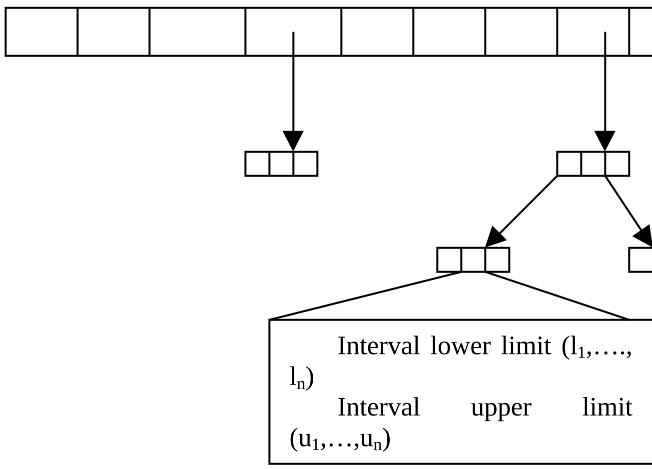


Figure 4: Data structure representation of the topographical knowledge.

When an environmental change event occurs, all links from the array become nil and the cell's best solutions are reevaluated and children generated for those cells that have improved in their fitness value. Each cell in the data structure contains an lower and upper ($[l, u]_1$,…,$[l, u]_n$) bounds f or the n variables indicating the ranges associated with the best solutions found in that cell so far, and a pointer to its children.

Acceptance Function

The acceptance function determines which individuals and their behaviors can impact the belief space knowledge. It is often determined as a percentage of the number of current individuals ranging between 1% and 100% of the population size, based upon selected parameters such as performance. For example, we can select the best performers (e.g. top 10%), worst performers (e.g. bottom 10%), or any combinations. Also, a modified dynamic acceptance function can be used by adjusting the number of accepted individuals over time, using the following function: $accept = top\left[p\% + \left(\frac{p\%}{k}\right)\right]$, where p represents the percentage of the population space that will affect the belief space; k is the number of time steps or generations in the current environment, and is reset to one with every environmental change.

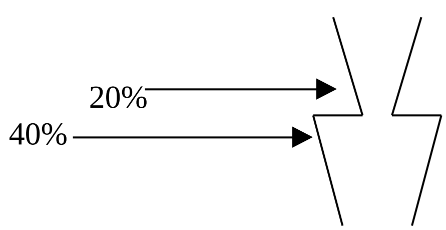


Figure 5: Changing Acceptance function

The idea here illustrated in figure 5 where the number of accepted individuals is doubled when k equals 1 in the above function. As k increases, the number of accepted individuals decreases. For example, if p in the acceptance function above set to 20%, then the number of the accepted individuals in the first generation (where k equals 1) will be 40% of the population space. In the second generation (when k equals 2), the number of accepted individuals is 30% of the population space.

Influence Function

In this section we develop several influence functions, one for each of the different knowledge structures. Some influence functions may be more useful than others depending on the dynamic behavior and the knowledge needed to track such behaviors. With more complicated dynamic behavior the system may need more than one type of knowledge and more than one influence function. The influence functions presented in this section may be used independently or in conjunction with other influence functions. We describe them in this section based on their increasing computational effort required.

Influence function using Situational and Domain Knowledge

This approach uses situational knowledge and knowledge about the problem domain to influence the mutation step size and direction. Before the first environmental change this influence function works similar to a function developed by Chung [1997] using situational knowledge only. When an environmental change occurs, our function generates increased diversity with a step size relative to the change magnitude in the environment. This function uses the domain knowledge to scale change in the best solution fitness value to the each parameter domain's ranges. For example, _ in figure 4.5 represents the change in the best exemplar when an environmental change occurs.

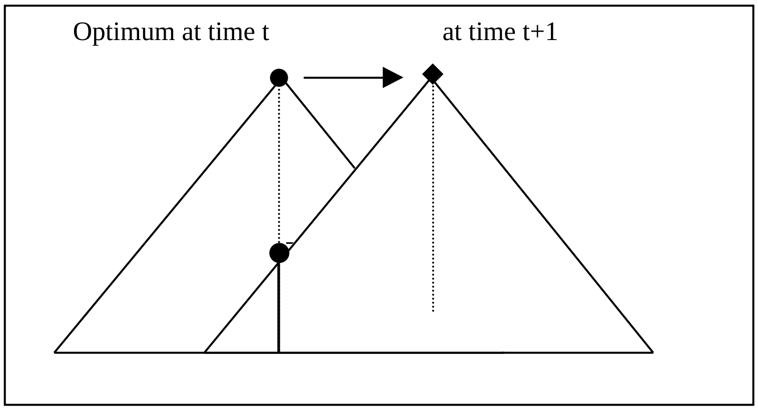


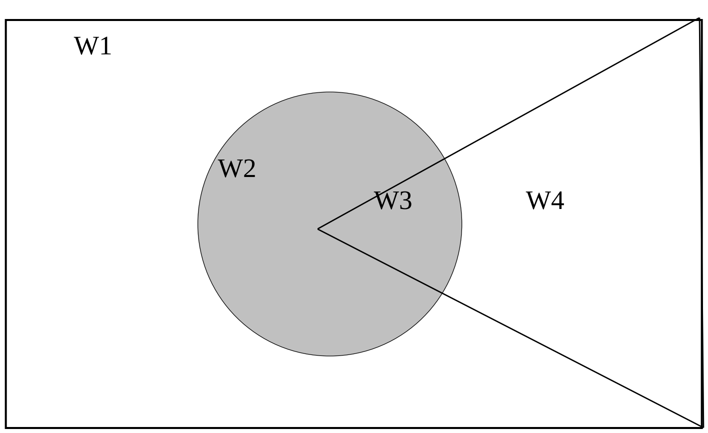
Figure 6: Optimum shift in one-dimensional landscape

This function uses the current best solution to influence the direction and the distance from the all time best solution to influence the step size. If there is no environmental change as yet, the current best and the best solution found so far will be the same and the function will use situational knowledge to influence the mutation step size and direction. After an environmental change occurs, _ is computed using the following function: $\lambda = |f(x_{best\_so\_far}) - f_i(x)|$. The next step is to scale the _ value to the parameter's ranges. The scaled _ can be computed as follow: $S\lambda_i = \frac{\alpha_i * \lambda}{f(x_{best})^t}$, where α_i is the value range for parameter i.

$$x_{p,j} = \begin{cases} x_{i,j} + S\lambda_j * random(0,1) & \text{if } x_{i,j} < E_j \\ x_{i,j} - S\lambda_j * random(0,1) & \text{if } x_{i,j} > E_j \\ x_{i,j} + S\lambda_j * random(-1,1) & \text{otherwize} \end{cases}$$

Influence function using Normative knowledge

This approach was originally developed by Chung [1997] for real valued function optimization in static environments. It is also useful for tracking the optimum in some types of dynamic behaviors where the change occurs within the parameter ranges. Since the normative knowledge represents the parameter range of the best solutions, it will be used to influence the direction of the search efforts within the promising ranges. The mutation step size is relative to the distance between the upper and the lower limit of each parameter.


W1
W2
W3
W4

Also, reevaluating and injecting the best solution from the history list into the population space when a change event take a place is useful in cases where the optimum returns to a previously visited location.

5.5 Influence Function using Topographical knowledge

The influence operator using topographical knowledge generates individuals from cells that are most likely to contain the optimum solution via using a roulette wheel approach to select the cells in which new individuals will be generated. Individuals are generated from best cell in the grid, any of the n best cells, or a random selection from any cell, relative to their weight (proportion) in the roulette wheel. The weights assigned for generating individuals from the best cell, the best n cells, and a random cell, are α%, β% and ϕ% respectively. The influence operator is given as follows:

$$x_{i,j} = \begin{cases} ranodm\,(bestcells\,[0].l_j, bestcells\,[0].u_j) & \alpha\% \\ ranodm\,(bestcells\,.l_j, bestcells\,.u_j) & \beta\% \\ ranodm\,(DL_j, DU_j) & \varphi\% \end{cases}$$

,where bestcells [0] is the best cell of the array of the best n cells sorted from top to bottom where best is stored in the cell number zero, and DL_j, DU_j are the lower and upper bounds respectively for parameter j.

Learning Influence Function priorities using a roulette wheel

Since the problem's dynamic behavior can have a great impact on the performance of any influence function, the system will use a roulette wheel to select the appropriate influence function (or functions) via adjusting the wheel area assigned to each type of influence function for a given class of dynamic behavior. The roulette wheel is initialized with an equal area for each type of influence function. For this study each type of knowledge is allocated a likliehood of 20%. The system will also, learn the influence function application schedule for environments that need more than one type of belief space knowledge. Learning the types of knowledge needed and the influence operators required with their application schedule for a class of problems dynamic behaviors can improve the performance quality and the time needed to achieve such quality.

The likelihood of using an influence function is based on size of the area under the wheel and the area for an influence function type is adjusted based upon its performance. The performance of an influence function can be computed via computing the average fitness value of all individuals generated by each influence function, as shown below:

$avr_i = \frac{\sum_{j=1}^{k} f_j(x)}{k}$, where k is the number of individuals generated via influence function i; $f_j(x)$ is the fitness value of individual i. Now, the influence operator is assigned an area of the roulette wheel relative to its average performance, computed relative to the average performance for all the influence functions:

$p_i = \frac{avr_i}{\sum_{j=1}^{n} avr_j}$, where p_i is a percentage on the roulette wheel assigned to influence operator i and n is the number of influence operators used in the system.

Combining the CA components into the CA Framework

The acceptance and the influence functions serve as communication channels between the belief space and the population space. The population space influences the belief space knowledge via the acceptance function, as shown in figure 8. The influence function controls the variation operators to guide the search. Figure 8 shows how a population-only model is integrated into the Cultural Algorithms framework.

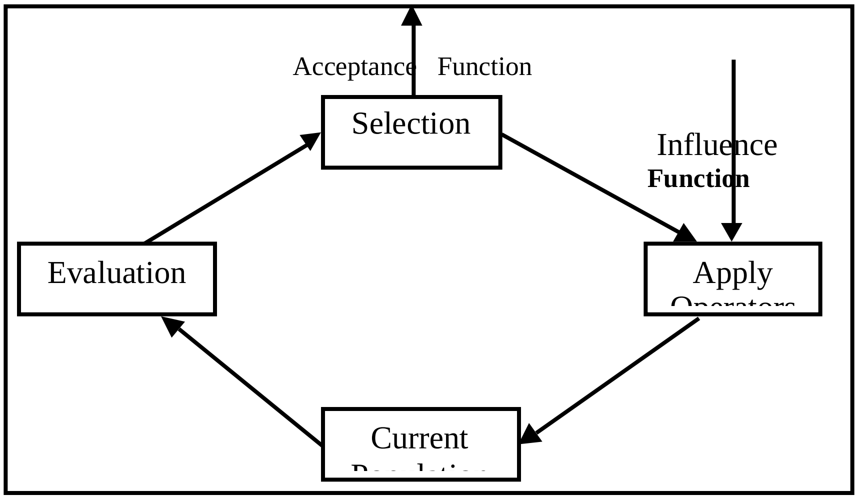


Figure 8 Integrated population level into the CA's framework

The basic algorithmic steps of our version of the Cultural Algorithms are:

- Generate random initial population of p individuals.
- Compute the performance score.
- Initialize the belief space.

Repeat.

- Select individuals with the current acceptance function.
- Update the belief space knowledge.
- Infer whether the environment has changed (by reasoning in the belief space) and update the environment history list accordingly.
- Update the roulette wheel weight assignment for each influence function in the system.
- Generate a new individuals using the appropriate influence function.
- Evaluate the new population.

Until (termination conditions are satisfied).

End

Results

In this section we investigate the performance of the system on a static and dynamic problem landscape. Its performance is compared with that of a self-adaptive EP system. The experiments were conducted using the dynamic problem generator of Morrison and DeJong [1999]. The generator produces a fitness landscape by locating cones of different dimensions on a two dimensional grid. Five experiments were conducted for both the static and dynamic environments in order to investigate the effect of increasing the number of peaks on the systems performance on the performance of the system and the knowledge types used. For each experiment, we generated twenty different random trials over the following dimensions:

Number of cones per experiment {4, 8, 16, 32, 64}.

Height range [3 to 6].

Slope range [2 to 7].

Location coordinates ranges [-1 to 1].

In the dynamic environment the parameters were reset randomly every 300 generations. .

Three basic phases of search emerged based upon the magnitude of improvements that were made by the operators. They were labeled as coarse grained, fine grained, and backtracking phases respectively. In coarse-grained environments relatively large increments in precision can be achieved by applying the influence functions in a generation. In fine grained situations, the best new individual exhibited small improvements, if any, in precision from one generation to the next. In the backtracking phase, additional variation introduced by the operations in respond to stagnation in the search process can lead to either a new coarse-grained phase or a fine-grained one. This stagnation could be due to having found the optimum or a false peak. Here, the system makes no distinction between the two, it merely increase variability when the system loses steam.

Coarse-grained phase

Figure 9 gives the percentage of generations that the influence function for each knowledge operator produced the best new individual for both static and dynamic environments. Note that in the coarse grained phase the influence function associated with the topographic knowledge plays the most important role in generating new solutions in both static and dynamic environments generating the best solution around 45% of the time over all 100 runs. The situational knowledge influence function was second contributing the best solution about 30% of the time. The other three is used much less frequently in both static and dynamic environments during the coarse grained phase. It is important to note that both topographic and history functions are more successful in dynamic environments than static ones with history knowledge success rate increasing about 5%.

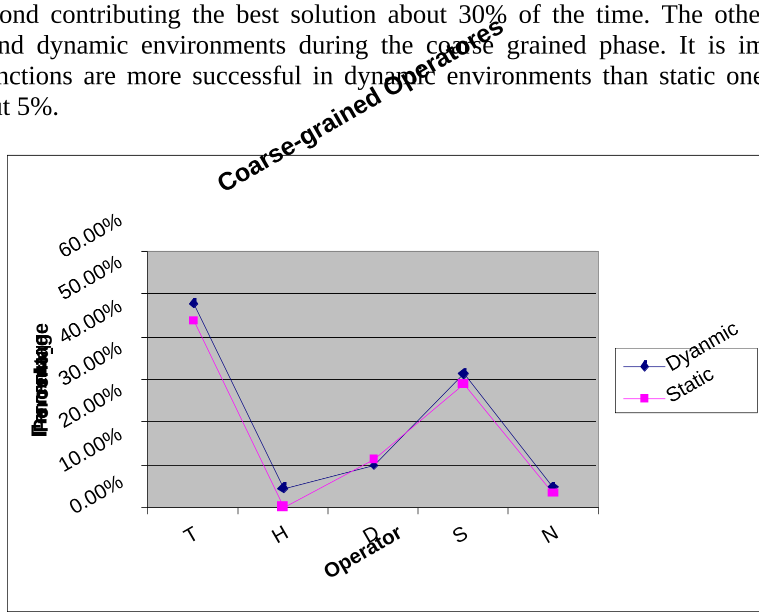


Figure 9 Knowledge Structures contribution comparison

The fine-tuning search phase

Figure 10 gives the relative percentage of the time that the influence function for each of the five knowledge sources was successful at producing the best individual in a generation. Notice that the participation of the influence functions is much different from that in the coarse grained environment. Again there is a basic similarity between the static and dynamic

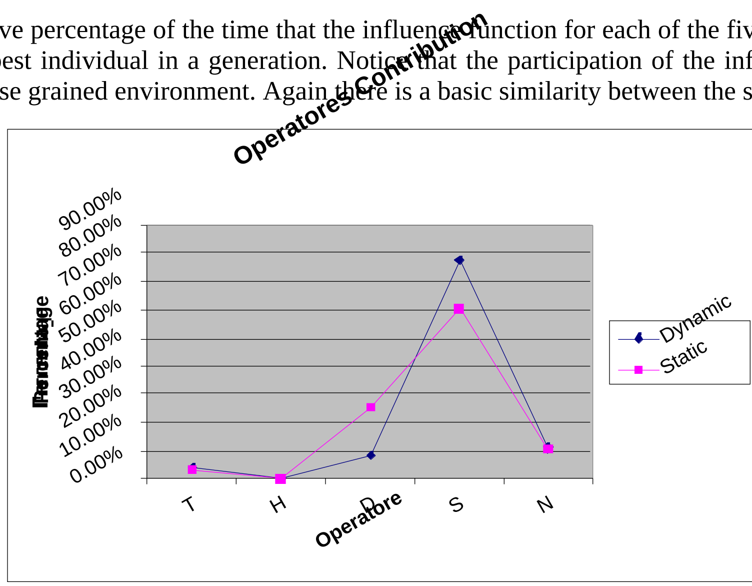


Figure 10 Knowledge Structures contribution comparison for static verses dynamic env.

environments, reflected here by the dominance of the situational influence function in producing the best new individuals with normative and domain knowledge also playing important roles. In the phase the topographic influence function is not very successful in producing the best solution unlike the coarse grained environment. The history function is likewise less productive here. Also notice that as we move froma static to a dynamic environment the success of the situational operator goes up substantially while the contribution of the domain operator goes down by about the same amount. This suggests that using the domain knowledge to make predictions is less successful when cone positions become more unpredictable. It is still a more important contributor to search in this phase than it is in the coarse grained phase. This makes sense relative to its role as a local knowledge source.

The Backtracking Search Phase

The backtracking phase search is activated when a no progress situation has been detected by the history knowledge or when topographic knowledge detects a change in performance. Table 1 gives the number of times that each of the influence functions was successful in generating the best solution at the onset of the backtracking phase. Once the backtracking phase has introduced new variation into the population the operator pattern tunrs either into that for coarse grained or fine tuning search depending upon the nature of the adjustment needed. Notice that all of the influence functions are successful in this phase except for the history function. This is due in part to that fact that the movements here are random in nature. If we added a cyclic pattern to the changes then it is expected that history would be much more important than it is here.

fun	**T**	**H**	**D**	**S**	**N**	**Total**	**T%**	**H%**	**D%**	**S%**	**N%**	**overAll%**
T:	**77**	**0**	**17**	**51**	**7**	**152**	**50.66%**	**0.00%**	**11.18%**	**33.55%**	**4.61%**	**22.45%**
H:	**0**	**0**	**0**	**0**	**0**	**0**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**
D:	**13**	**0**	**15**	**12**	**2**	**152**	**8.55%**	**0.00%**	**9.87%**	**7.89%**	**1.32%**	**22.45%**
S:	**44**	**0**	**15**	**79**	**62**	**200**	**22.00%**	**0.00%**	**7.50%**	**39.50%**	**31.00%**	**29.54%**
N:	**23**	**0**	**13**	**38**	**99**	**173**	**13.29%**	**0.00%**	**7.51%**	**21.97%**	**57.23%**	**25.55%**

Table 1. Sequence transition table for the Backtracking search phase

Conclusions

In this paper we have investigated the relative use of different knowledge sources in the tracking of the optimum in real-valued function optimization problems using Cultural Algorithms. In 100 runs over environments of between 4 and 64 randomly moving cones, certain patterns of knowledge source activity emerged. Three basic phases of problem solving activity were identified in terms of the relative involvement of the five operators: coarse-gained, fine-tuning, and backtracking. Three of the knowledge sources had previously been used in static environments while domain and history knowledge were added to address issues of local and global dynamics respectively. The domain operator was the more important of the two here. Since the changes were random there were few global patterns for the history knowledge to detect. As more patterned change is introduced into the scenario one would expect that the role of history knowledge will become much more important.

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Systems Dynamics, Evolutionary Principles and a Sociocultural Algorithm: Answering a Weberian Question

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One of the main questions Max Weber dealt with is that of the European *Sonderweg* (special way), i.e., the question why only in Europe emerged that particular form of society which is known, e.g., as industrial capitalism, functionally differentiated societies or parliamentary bourgeois democracies and why other societies stagnated compared with the dynamical evolution of the European culture. A lot of scholars have tried to answer it in different ways (cf. Trigger 1998) but no answer has been found which places the European way into the frame of a *general* theory of sociocultural evolution.

By comparing the situation of medieval Europe with the Chinese or Islamic societies one main difference is rather obvious: the feudal Europe was much more differentiated than its contemporary rivals – Emperor versus Pope, free towns versus noble landowners, the difference and rivalry between the single nations and so forth. This empirical observation leads to a general *hypothesis of heterogeneity*: the more heterogeneous a society is the more probable is its sociocultural evolution, that is its reaching new levels of sociocultural development and vice versa.

Jörn Schmidt and I translated this hypothesis into a mathematical model, a so called *sociocultura l algorithm* (SCA) and tested it by computer simulations. Basically the SCA is a generalized cellular automaton (CA) whose cells represent the occupants of social roles. The interactions between these artificial actors ("agents") are defined as social learning, i.e. the taking over of knowledge and particular problem solving strategies, the inhibitings of problem solving capabilities and the mutual reinforcing of the occupants of the same role in a common geometrical neighborhood. Inhibiting mean that the occupants of certain social roles like priests, teachers or politicians (so called cultural roles) have "damping" effects on other actors, i.e., they restrict the creative abilities of those actors to the limits of the respective culture. Reinforcement means that occupants of the same role can compensate to a certain extent the inhibiting effects of the cultural roles. Generating and changing of roles are regulated by "exogeneous" parameters, i.e. the orientation of the artificial society to environmental demands and "endogeneous" parameters which mean the effects of the geometrical distribution of role occupants on the grid of the CA. I shall give some more details about the SCA and its theoretical foundations in my lecture.

Our experiments confirmed the hypothesis of heterogeneity in the sense that the evolution of our artificial societies depends indeed on a particular form of heterogeneity, that is the relations between the inhibiting effects and the reinforcing ones. These can be interpreted as the degree of role autonomy, i.e., the degree of role differentiation in a particular society. Therefore we concluded that the hypothesis is a sound one.

When looking in a systems theoretical way at this hypothesis one can see that it indicates an even more general aspect of evolution. Our experiments demonstrate that the relation between the different effects generates evolution as the emerging of new sociocultural levels only in certain cases, i.e., if the degree of role differentiation is already rather high. Even the differentiated society of medieval Europe could not have such degrees at its beginnings. Therefore we had to assume that the degree of differentiation is itself *the effect of the evolution of the same sociocultural system whose evolution the degree generates.* In other words, sociocultural evolution must be understood as a process by which a system is able to vary the initial conditions of evolution it started with.

If this consideration is valid then sociocultural evolution must be seen as a new form of dynamics which has no counterpart in the dynamics of physical and biological systems. Physical systems can be described by a concept of *first order dynamics,* that is dynamics as successions of states which are generated by constant rules of interaction. Biological systems exhibit a *second order dynamics* which means an adaptive dynamics with variable rules according to certain environmental conditions. First and second order dynamics can be classified: first order dynamics is dependent on certain ordering or control parameters respectively (Kauffman 1993) which in turn are representations of a general aspect of inequality of first order systems (Klüver 2000). Second order dynamics can be classified by so called meta parameters (Klüver loc.cit.) which measure the adaptive capabilities of these systems.

Sociocultural (and cognitive) systems apparently are characterized additionally by a third order dynamics , i.e., a dynamics which is not only generated by the principles of first and second order dynamics but also by the capability to change its own evolutionary initial conditions in dependency on the state of its evolution. The European special way demonstrates that this ability is in turn dependent on favorable initial conditions: only the initial heterogeneity of medieval Europe enabled the European societies to develop its third order dynamics. Informal considerations of Bateson (1972) about social and cognitive ontogenesis suggest that this is the case in the ontogenesis of cognitive systems also.

The "evolution of the universe" is also the emerging of different kinds of dynamics as the succession of first, second and third order dynamics (physical, biological and sociocultural/cognitive systems). Interestingly enough it seems that sociocultural evolution repeats in this respect the "universal" evolution: the early tribal societies of hunter-gatherers can be taken dynamically as representatives of first order dynamics; the agrarian state empires are examples of systems with second order, that is adaptive dynamics; finally the modern societies of the Western kind can be understood only as the unfolding of third order dynamics - a rather sophisticated form of selfreferentiality which is able to change the states, the rules *and* the evolutionary conditions of the sociocultural systems. Therefore the question of Max Weber can be answered indeed in a very general way: the case of the European *Sonderweg* is special because only in this case certain initial conditions were such that third order dynamics could emerge and regulate the evolution of the Western societies.

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Toward a Computational Theory of Equilibrium Selection

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This paper considers the notion of equilibrium, very familiar to game theorists and economists, from an empirical perspective. When considering real world organizations or institutional analysis, predictions should satisfy three fundamental requirements. Predictions must be robust to small perturbations of any relevant environmental variables, based on agents' use of behaviorally realistic strategies, and distributional in nature (so as to be meaningfully falsifiable). The model presented here presents the beginnings of a jointly analytical and computational approach towards equilibrium predictions satisfying these requirements. The game theoretic concept of Nash equilibrium is used as the baseline for comparison and discussion. The defining characteristic of Nash equilibrium is the self-enforcing aspect of all agents' strategies -- given what every other agent's strategy choice, no agent can unilaterally deviate and strictly increase her payoff. The extension of this intuitive criterion to environments where the mapping from strategies to payoffs changes in a dramatic and unpredictable fashion is not straight-forward and often leads to empirically unsupported equilibrium predictions in such environments. The difficulty lies in the sensitivity of equilibrium predictions to informational structures and the inherent uncertainty regarding the environmental variables underlying any real world situation. Given that the uncertainty faced by the analyst generally also confronts the agents being studied, any proper notion of equilibrium for the empirical study of organizations and institutions must take into account the agents' mental models.

Notions of equilibrium serve (at least) two purposes: normative and predictive. Normatively, a notion of equilibrium characterizes what agents in a particular strategic situation should do if their motives and abilities satisfy a specified set of assumptions. From this standpoint, equilibrium analysis is a logical inquiry: the deductions derived in equilibrium analysis can not be falsified. Indeed, I argue that this application of equilibrium analysis is one of the cornerstones of analytical social science. Conversely, the predictive role of a notion of equilibrium is frequently misunderstood. An equilibrium "prediction" can be expected to be correct only insofar as the assumptions regarding agents' motivations, abilities, and understanding of the strategic situation are valid. Accordingly, the appropriate interpretation of rejecting an equilibrium prediction is as a rejection of at least one of the assumptions underlying the equilibrium analysis as opposed to the notion of equilibrium itself which, as a definition, can not be falsified.

I discuss several difficult issues that any scientist who wishes to apply equilibrium analysis to a study of real-world strategic situations must confront. Briefly, these problems include multiplicity of predictions, incomplete measures of robustness, and the difficulty presented by unknown heterogeneity. In addition, I discuss the notion of common knowledge which are required by most game theoretic definitions of equilibrium to ensure that their predictions are mimicked in play by rational players. I argue that this analytical linchpin of Nash equilibrium is the most easily refuted assumption underlying equilibrium analysis.

The primary message of this paper is that small changes in the environment may lead to very large changes in observed behavior -- especially when these changes affect the information available to the agents. Furthermore, the point is not that changes which appear small are actually quite significant; rather, the nonlinearity of best response dynamics renders a simple (or even continuous) mapping of environments into outcomes generally impossible. In this paper, I present the beginnings of an exploratory model of equilibrium selection which is partly based on computational analysis of social situations. I argue that equilibrium analysis for the purposes of prediction is most effectively carried out by incorporating the increasingly robust findings of psychology and behavioral economics, along with the fundamental uncertainty faced by any analyst of real-world organizations and strategic situations, into a simulation-based, probabilistic framework.

— Extended Abstract —
Computational Analysis of Brand Marketing

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1 Introduction

In order to survive intense competition with other companies, it is important for a company to consider *brand marketing* that includes brand strategies and management [Harvard Business Review 1999]. This is because brand strategies and management have the potential to enhance the brand effects of a bran name, trademark, brand image, and so on. These effects led companies to recognize the importance of brand marketing. However, such recognition is based not only on the above brand effects but also on the following factors [Ichihashi 2000, Yasuhara 2000]: (1) a demand of new types of goods for the full growth of markets; (2) marketing strategies based on consumer trends due to the current purchase criteria of consumers that change frequently; (3) dynamically changing market structures due to the influence of IT (Information Technology); and (4) a shift towards placing an importance on profits by focusing on long-selling goods that are purchased continuously rather than great hit products that are purchased temporarily.

Due to these factors, the conventional and traditional brand marketing can no longer bring desired brand effects. Furthermore, the brand marketing of a commonly accepted theory, a popular opinion, or a common view may no longer be valid. Accordingly, how do we take on today's complex and dynamic markets? This is one of the major issues to clarify in organizational and management science. To find solution to this issue, a lot of research on *case study approaches* has been reported in recent years [Harvard Business Review 1999]. However, this kind of research cannot easily capture the essential parts of brand marketing because each brand strategy and management focus is specific to each company. To overcome this problem, we employ an *agent-based approach* [Axelrod 97] for an objective analysis of complex and dynamic markets by computational techniques. Through an investigation based on agent-based approach, this paper gives some implications from a computational analysis of brand marketing.

2 Brand Marketing

We may believe that the term *brand* is typically used for high-quality or expensive goods like *Chanel*, *Burberrys*, and so on. However, this term is actually a general term of several values on a good. According to Yasuhara, the brand is composed of the following three values [Yasuhara 2000].

- **Fundamental value:** This value implies an essential part of a good. For instance, taste is one of the fundamental values of beer.
- **Information value:** This value is related to an image of a good. For instance, a label of cans is one of the information values of beer.
- **Surrounding value:** This value is not directly related to a good. For instance, recyclable cans are one of the surrounding values of beer.

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Considering the above values, companies should appropriately combine these three values to produce goods that are clearly distinct from other goods and should provide strong images of the goods to consumers. This is because such goods can contribute to creating *repeaters* who continuously purchase the goods. This is the main aim of brand marketing.

3 Agent-Based Brand Marketing Model

Based on the three brand values described in the previous section, we propose an *Agent-based Brand Marketing (ABM) Model* for a computational analysis of brand marketing. In this model, the following two types of agents are employed:

- **Company agents:** These agents produce products.
- **Consumer agents:** These agents purchase products they want to obtain.

In the agent architecture, the company agents are implemented by one simple rule, *i.e.,* to produce products when orders are received from the consumer agents. The consumer agents, on the other hand, are implemented by a Learning Classifier System (LCS) [Goldberg 89] and have the following components: (1) an image of a target product; (2) rule sets composed of a lot of *if-then* rules with weight factors; and (3) learning mechanisms including reinforcement learning and GA operations.

Here, we define that a product is represented by the three brand values with their ranges limited from 0 to 100. Based on this definition, the company agents produce products by setting the three brand values to match a total fixed value. For instance, a company agent produces a product by setting the fundamental, information, and surrounding values to 50, 50, and 100, respectively, when the total number of the three brand values is fixed to 200. Similarly, the consumer agents have their own target products based on the three initially set brand values, and purchase a product if the three brand values of a manufactured product are close to those of a target product. To purchase better products, the consumer agents improve rules and varies their weighs through the learning mechanisms.

4 Simulation

Using our ABM Model, we conduct the following simulations.

(1) **Product preference:** This simulation compares the differences between strong and week preferences to products in the consumer agents. The degree of preference is determined by the matching range of rules.

(2) **Learning speed:** This simulation compares the differences between fast and slow learning in the consumer agents. The learning speed is determined by the execution span of GA operations.

In each simulation, we investigate how a new product is purchased in comparison with other products. This new product is introduced by a new company agent after 100 iterations, *i.e.*, the situation where the consumer agents have already purchased 100 products through the learning of better purchasing rules. This situation implies a difficult environment for a newly introduced product. In the experimental setting, the following parameters are set: (1) the numbers of company and consumer agents are five and 100, respectively; (2) a new company agent is added after 100 iterations; and (3) each company agent produces one product.

Through intensive simulations, we found the following implications: (1) in the product preference simulation, a newly introduced product obtains a large share when consumer agents have a strong preference to the product; and (2) in the learning speed simulation, a newly introduced product obtains a large share when the learning speed of consumer agents is high.

5 Discussion

(1) Product preference

The first simulation result indicates that a newly introduced product can obtain a large share when consumer agents have a strong preference to the product. What does this result mean from the viewpoint of brand marketing? Considering the fact that the degree of preference is determined by the matching range of rules, we can roughly assume that a market is growing in the case of a weak product preference while the market reaches full growth in the case of a strong product preference. This can be easily understood by considering that we can select the best product using a lot of information in a full growth market. Although the opposite result is obtained when investigating the result from the viewpoint of the iteration count, such a result is only valid in a short range of the time scale and not in the large range that determines the growing or full growth market. Based on this consideration, the first simulation result shows that a new company has the possibility to obtain a large share even in a full growth market. This result is clearly different from a common view of brand marketing.

(2) Learning speed

The second simulation result indicates that a newly introduced product can obtain a large share when the learning speed of consumer agents is high. What does this result mean from the viewpoint of brand marketing? Considering the fact that learning generally provides an adaptation to various situations, we may take the obtained result for granted. However, what we should note here is that the learning in computational science also promotes agents to be specialized in the current situation through an adaptation process. This means that a market with a high learning speed does not easily adapt to various situations, *e.g.*, a market for old aged persons while a market with a low learning speed more easily adapts to various situations *e.g.*, a market for young persons. Based on this consideration, the second simulation result shows that a new company has the possibility to obtain a large share even in a market for old aged persons. This result is also different from a common view of brand marketing.

6 Conclusion

This paper proposes the *Agent-based Brand Marketing (ABM) Model* and investigates brand marketing through a computational analysis. From two simulations on the product preference and the learning speed of consumer agents, this paper arrives at the following conclusions: (1) a new company has the possibility to obtain a large share even in a full growth market or in a market for old aged persons; (2) the results in this paper differ from common views of brand marketing, through different interpretations involving time span and term learning; and (3) careful interpretation of computational results should be taken when analyzing brand marketing.

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The Lost Performance of Misfits: A Dynamic Approach to Fit and Firm Performance

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In this study we will develop and empirically test a dynamic approach to examining the relationship between strategic and organizational misfits and firm performance. Utilizing an expert system, OrgCon, misfits are identified for six U.S. bank holding companies using eight semi-annual periods of data from 1996 to 2000. Quantitative and qualitative techniques of data collection are applied to publicly available data to obtain inputs for OrgCon. Longitudinal analyses are applied to analyze the dynamic relationship between each bank's misfits and its financial performance.

DYNAMIC FIT APPROACH

We propose a dynamic approach to the study of fit and firm performance that simultaneously assesses all dimensions of an organization over an extended period of time, providing several advantages over traditional approaches to fit. First, as with systems and configurational approaches to fit, the dynamic approach takes a holistic perspective of the organization, providing a more complete picture of the interaction between dimensions that impact the organization. This allows for the comparison of the benefits of reducing misfits in one dimension to the costs of potentially creating additional misfits in another dimension. Longitudinally, this approach explores the dynamics of changes in misfits and performance as well as assessing both short and long-term consequences of changes in organizational misfits.

This dynamic approach raises many interesting streams of research. One such stream is how do changes in the type and number of misfits impact performance? Fit theories argue that there is an inverse relationship between misfits and performance. However, we will explore the possibility of increasing performance by intentionally creating misfits in an attempt to realign an organization with its environment. Similarly, one could examine the magnitude of the change in performance in response to changes in misfits. For example, is there an optimal magnitude of change for a given period, where too much or too little change will result in undesirable changes in performance ? Another stream of research is to examine the sensitivity of changes in firm performance to changes in given organizational dimensions. One such question might be do organizations exhibit greater increases in performance through the reduction of misfits related to climate than misfits related to structure or strategy?

RESEARCH DESIGN

We will attempt to answer these questions by first assessing how misfits in one period affect performance in the same and subsequent periods by collecting both quantitative and qualitative publically available data on a number of organizations over an extended period of time as input data for the OrgCon expert system. Based on the management, organization, and strategy literatures, OrgCon will use these data as inputs for its inference engine to diagnose misfits, which will help to significantly reduce the complexity of the scope of this project. These misfits then become the independent variables upon which our performance measures, return on assets, are regressed.

Public data will be collected from diverse sources, including data that are provided by the firms themselves (i.e. SEC filings, annual reports, company websites, and press releases) as well as data from the popular press (i.e. The Wall Street Journal, Business Week, and The Wall Street Journal Review), online financial service providers (i.e. Hoovers, Standard & Poor's, and Motley Fool) and career insiders (i.e. WetFeet Press and Vault.com). Online search engines, databases such as ABI-Inform, EBSCOhost, or Lexis-Nexis, and company homepages, in addition to scores of other site, will be used to locate articles and retrieve data.

SAMPLE

U.S. bank holding companies (BHCs) are among the most heavily regulated companies in the United States, and dramatic shifts in their environment have resulted in a tremendous amount of change in not only organizational structure and strategy, but in nearly all facets of organizational life. The most dramatic impact of deregulation has been the unprecedented increase in the number of mergers and acquisitions within the industry. This trend is not limited to only the acquisition of other banks, but to firms in all financial service industries. In addition to deregulation, advances in technology, such as more powerful computing, sophisticated banking applications, and the internet, have made available to banks not only a tremendous amount of additional data—both on in the industry and on customers and clients—but the ability to analyze this data to achieve greater efficiencies and provide greater customer service. Finally, the improvement in financial conditions in the U.S. has had a significant influence on the banking industry. Low interest rates and high stock prices, as well as high profitability, have allowed for greater merger and acquisition activity. Combined, we believe these four factors contribute to an environment that fosters change in an industry, and it is each BHC's response to this highly dynamic environment that we believe will allow us to observe change in misfits and their impact on performance.

Platform Externality and Lock In

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1. Platform Goods and Service Goods on the Platform

In this paper we introduce the concept of platform externality which is an extension of the concept of network externality. Network externality is a classical notion for competition among network, where the utility of goods or service on a network depend on the market share of the network. It is also used. The notion is used for analyzing the competition of standard such as VHS vs. Betamax [Katz,1986; Cornes, 1996]. We extend the notion of network externality to the vertical reliance between service goods and its platform. We assume two types of platforms such as α and β. In this paper we focus on companies who provide service goods on the platforms and consumers who buy both platform and service goods at first. We treat the competition among companies who provide platforms in the last part.

The service providers have three alternatives as follows. “b1” , “b2” and “b3” means that the companies provide service goods on the platform α, β and both respectively. The consumers have the following three alternatives. “a0” is a dummy alternative which denote the initial condition which mean they have nothing. “a1” and “a2” denotes the selection of platform α and β respectively.

The following table 1 shoes w the average payoff of consumers for each alternative. The table 2 shows the average payoff of service providing companies for each alternative.

Table 1 Average Payoff for Alternatives of Consumers

Average Payoff	From Service Goods	From Platform Goods
E[a0]	0	0
E[a1]	K10 + K11P[b1] + K11P[b3]	h10 + h11Q[a1] -d1
E[a2]	K20 + K21P[b2] + K21P[b3]	h20 + h21Q[a2] -d2

Table 2 Average Payoff for Alternatives of Service Providers

Average Payoff	Benefit from Selling Service Goods	Cost from Providing Service for Platform
E[b1]	r10 + r11Q[a1]	-C1
E[b2]	r20 + r21Q[a2]	-C2
E[b3]	r30 + r11Q[a1] + r21Q[a2]	-C3

Total verage payoff of consumers E[a] and service providers E[b] are shown as follows.
E[a]=Q[a0]E[a0]+Q[a1]E[a1]+Q[a2]E[a2]
E[b]=P[b1]E[b1]+P[b2]E[b2]+P[b3]E[b3]
Where Q[ai] and P[bj] denote the population ratio for each alternative in consumers and service providing companies respectively. Then we induce the following Repricator dynamics which show social learning process of agents [Deguchi, 1998;2000].

dQ[a1]/dt={Q[a1](E[a1]-E[a])} dQ[a2]/dt={Q[a2](E[a2]-E[a])}
Q[a0]=1-Q[a1]-Q[a2]
dP[b1]/dt={P[b1](E[b1]-E[b])} dP[b2]/dt={P[b2](E[b2]-E[b])}
P[b3]=1-P[b1]-P[b2]

This model includes two types of externalities. The one comes from the share of platform by consumers and the other comes from the share of platform by providers. We add small fluctuation in the simulation. In our model C1, C2, C3 denote a cost for providing service goods on the platform α, β and both platform respectively. Thus $Max(C1,C2) \le C3 \le C1+C2$ holds. We assume C1=C2=C and $C \le C3 \le 2C$ for simplification. h10 and h20 show technological utility of each platform respectively. d1 and d2 denote cost of platform α, β for consumers per period respectively.

The simulations are shown as follows. We assume such initial conditions about the share of platforms by consumers as α =11% and β =10% in figure 1. We also assumed C3=1.7*C1, C1=C2=0.1 at table 2 and h20 = 0.1 at table 1.
Figure 1 shows the effect of the fluctuation on initial share. As a result Q[a2] and P[b2] become 1 under the small difference of initial share condition. Q[a2] and P[b2] might become 1 under the small perturbation.

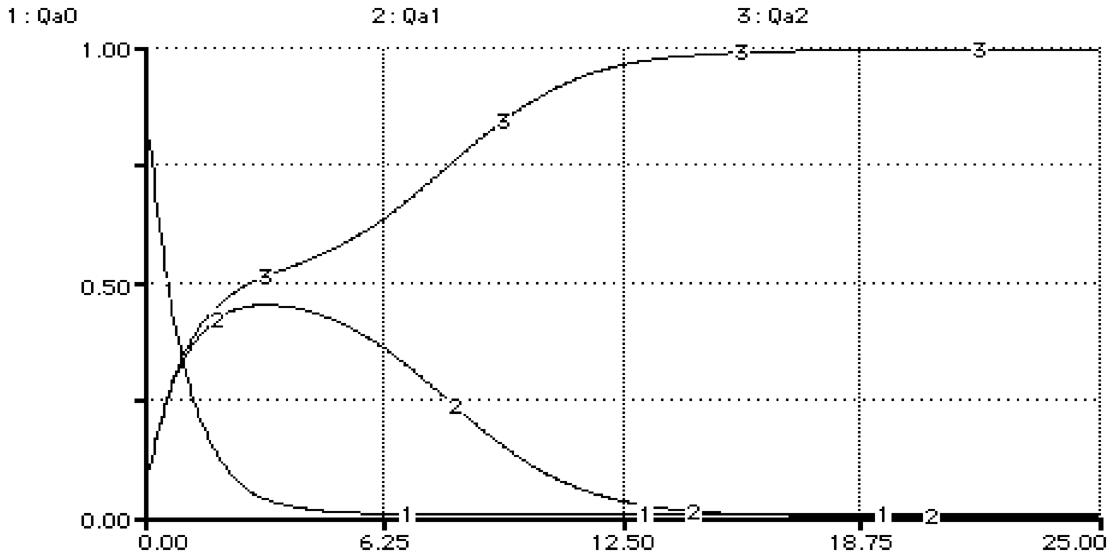

Figure 1 Platform Selection by Consumers

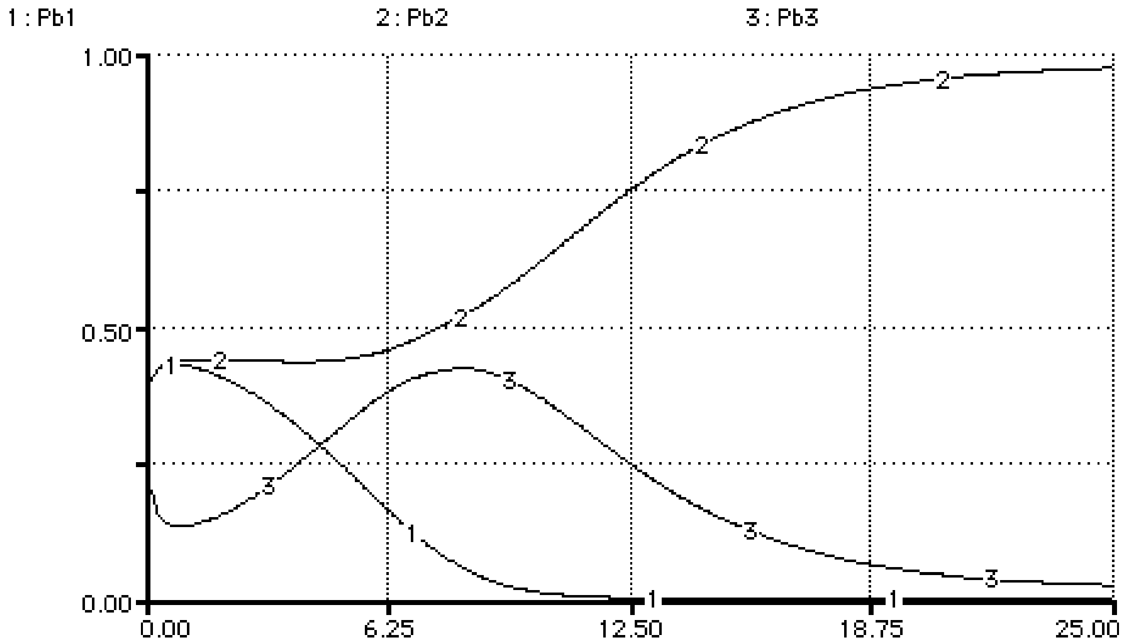

Figure 2 Platform Selection by Service Providers

There happens strong lock in. The monopoly comes from the dynamical change of demand depending on the share of platform by consumers and service providers and on its mutual interaction. This type of monopoly dose not come from supply side effects by platform providing industry such as economy of scale or scope. It comes from dynamic change of utilities of consumers and service supplier s on the platform and its mutual learning dynamics. Thus we call this demand oriented monopoly.

3. Bifurcation Analysis of Learning Dynamics

dQ[a1](t)/dt=Q[a1]({E[a1]-E[a]}=Q[a1](1-Q[a1]){E[a1]-E[a2]}
The stability of this dynamics depends on the sign of {E[a1]-E[a2]}.
E[a1]-E[a2]=K10 + K11P[b1] + K11P[b3]+h10 + h11Q[a1]-d1
-K20 - K21P[b2] - K21P[b3]-h20 - h21Q[a2]+d2
Let h21 = h11= h1, k11 = k21 = k1, K10=K20.
If there is no competition of cost and technology among platform providing companies then we assume that d1=d2=d, h20 = h10=h0.
Then E[a1]-E[a2]= h1{Q[a1]- Q[a2]}+k1{P[b1] - P[b2]}
=h1{2Q[a1]- 1}+k1{P[b1] - P[b2]}.
Let P[b1]=P[b2]=0. This means there is no additional cost for providing service goods to both platforms.
Then E[a1]-E[a2]=h1{2Q[a1]- 1} holds. Q[a1]=1/2 is an unstable equilibrium point.
Q[a1]=0 and 1 are stable solution. Thus the share of platforms is locked depending on initial share.
Now we consider the competition of the price and technology between platform providing companies about platform selection . If we assume that there is no crossover cost for providing service goods to both platforms, i.e. C3=C1=C2=C. Then P[b1]=P[b2]=0 holds.

Proposition 3.1
E[a1]-E[a2]=h1*{2Q[a1]- 1}+k1*{P[b1] - P[b2]}+d1-d2+h10-h20.
Let Δ=d1-d2+h10-h20. Then
(1) If (h1-Δ)/2h1 $\le$ 0 $\Leftrightarrow$ h1 $\le \Delta$ then Q[a1]=1 is stable.
(2) If 1 $\le$ (h1-Δ)/2h1 $\Leftrightarrow$ $\Delta \le$ -h1 then Q[a1]=0 is stable.
(3) If 0 $\le$ (h1-Δ)/2h1 $\le$ 1 $\Leftrightarrow$ -h1 < Δ < h1 then Q[a1]= (h1-Δ)/2h1 is unstable.
Proof:
E[a1]-E[a2]=h1*{2Q[a1]- 1}+k1*{P[b1] - P[b2]}+Δ.
E[a1]-E[a2]=2h1*Q[a1]- h1+Δ holds. Thus
Q[a1]=1 is stable $\Leftrightarrow$ 0 $\le$ E[a1]-E[a2] $\Leftrightarrow$ (h1-Δ)/2h1 $\le$ 0 $\Leftrightarrow$ h1 $\le \Delta$
Q[a1]=0 is stable $\Leftrightarrow$ E[a1]-E[a2] $\le$ 0 $\Leftrightarrow$ 1 $\le$ (h1-Δ)/2h1 $\Leftrightarrow$ $\Delta \le$ -h1
Q[a1]= (h1-Δ)/2h1 is unstable $\Leftrightarrow$ $\Leftrightarrow$ 0 $\le$ (h1-Δ)/2h1 $\le$ 1 $\Leftrightarrow$ -h1 < Δ < h1
Q.E.D.

Thus Q[a1]= (h1-Δ)/2h1 is a equilibrium point.
Let h1=0 then stable pint will change depending on the sign of Δ. Δ is determined by pure competition. If the competition of price and technology change the sign of Δ then stable equilibrium point will change by the competition. This means the competition is something fair.

If h1 is not zero then there happens a barrier for fair competition which has 2h1 in depth. The barrier was caused by platform externality. In this case the coexistence of platforms is difficult to achieve because of its externality.

3. Conclusion

Platform externality causes demand oriented monopoly of the platform and service goods on the platform. It causes unfair competition situation. To avoid this we have to introduce cross platform policy in some way. The model provide the tool for analyzing the industrial policy on the platforms and service goods on the platforms.

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Modeling and Simulation for Work System Design

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Introduction

Work systems are systems in which humans, computer, robotic, and other systems, artifacts, and space come together performing activities over time to produce goods, services or, as is the case in the work system described in this paper, scientific discovery. The work systems we encounter everyday have mostly existed over a long period of time. Improvement of such work systems is often done through business process analysis and reengineering (Hammer and Champy, 1993) (Davenport, 1993). Seldom do we face the design of a work system that does not exist. In this paper we describe the initial design of a work system that does not yet exist. The work system to be designed is a mission operations system for a proposed NASA discovery mission to the Moon with a semi-autonomous rover.

The use of M&S in work system design

Due to the continued increase of computing power, many engineering disciplines now make use of powerful computational modeling and simulation (M&S) tools. The benefit of computational modeling is that it allows for the creation of virtual prototypes of the designed system. On top of this, computer simulation allows us to investigate the behavior of a virtual prototype, and thus understand the strengths and weaknesses of the design of the system over time. Using M&S is particularly effective when the complexity, time and cost of creating and testing a design of a system with real-world physical prototypes, is extremely high (Zeigler et al., 2000). M&S of work systems falls in this category.

The complexity and cost of creating a real-world simulation of a work system is extremely high. We claim that using the Brahms tool in the design process of work systems allows us to test work system designs that could not easily be tested before its actual implementation and operation. In high-risk NASA missions such a capability would be extremely useful. This obviously has a huge potential in helping to solve one of the most often cited causes in NASA mission failures [ref. Challenger accident report and Mars Polar Lander failure report].

Work Practice

Often people view work merely as the process of transforming input to output, i.e. a Tayloristic view of work. In contrast, a work practice is defined as the collective activities of a group of people who collaborate and communicate, while performing these activities synchronously or asynchronously (Clancey, 1998). We are interested in describing work as a practice, a collection of psychologically and socially situated collaborative activities between members of a group. We try to understand how, when, where, and why collaborative activities are performed, and identify the effects of these activities, as well as to understand the reasons why these activities occur in the way they do. Therefore, the central theme is to find a representation for modeling work practice. Brahms is a M&S environment for representing a work process at the work practice level using a multiagent rule-based activity language, that can be simulated using the Brahms simulation engine (Sierhuis, 2000) (Sierhuis et al., 2000b) (Sierhuis et al., 2000a).

This paper discusses how we have used Brahms to design the work system for the proposed Victoria mission. The attentive reader might question how we can *design* a work practice? Indeed, a work practice is not designed. Instead, it evolves over time. However, what we are interested in studying is how a model of the design of a work process at the practice level, can be used in the design of the mission. We believe that a model at the work practice level allows us to represent the future work system in a more realistic manner, because it takes a holistic approach to the representation of work (Clancey et al., 1998) (Clancey, 1997a) (Clancey, 1997b) (Sierhuis and Clancey, 1997). It represents individual agent behavior, group behavior, and collaboration, as well as the use of tools, artifacts and where they are located during the actual work. This is in contrast to other work process and knowledge modeling paradigms (Tyo, 1995). Next, we discuss the Victoria case study.

Victoria Mission

Victoria[1] is the name of a proposed long-term semi-autonomous robotic mission to the South Pole region of the Moon. At the start of this case study the Victoria team was in the middle of writing the proposal. Team members (so called Principal Investigator and Co-Investigators) of the Victoria mission are world-renowned scientists from different scientific disciplines (planetary scientists geologists, robotisists, and AI-specialists).

From this scientifically important objective, the Victoria team decided that the most efficient way to meet this science objective is to use a high-speed semi-autonomous rover that can traverse over long distances (several hundreds of kilometers), for a long time period (three months to a year), to gather the necessary geological and physics data (Cabrol et al., In press) (Spudis, 1999).

The Victoria Rover

The Robotics Laboratory at Carnegie Mellon University is developing the Victoria Rover. One of the biggest constraints in any robotic mission is power consumption of the robot. A robot gets its energy from onboard batteries. These batteries are charged by solar energy, using large solar arrays on the robot. In every activity the rover uses energy, therefore the sequence of activities for the rover is constraint by the amount of power available to complete the sequence. When the robot's batteries are low, it needs to return to a sun-exposed spot in order to recharge its batteries. Batteries are heavy artifacts that need to be brought up in space, and are therefore limited in size and power. This makes the whole robot power consumption issue a very important constraint in the design of the

[1] The name Victoria was chosen after the only ship of Ferdinand Magellan's voyage that circumnavigated the world. Ferdinand Magellan, (1480?-1521), Portuguese-born Spanish explorer and navigator, leader of the first expedition to circumnavigate, or sail completely around, the world.

robot, but also a very important constraint in the ability of the robot to perform certain activities during the mission, given a particular mission operation work system.

Victoria Mission Operations Work System

Figure.1 gives a pictorial representation of the known work system elements and their relative geographical location during the Victoria mission. The Science Team consists of a number of sub-teams, all co-located in Building 244 at NASA Ames Research Center, Moffett Field, California. The sub-teams are the Science Operations Team (SOT), the Instrument Synergy Team (IST), and the Data Analysis and Interpretation Team (DAIT). There are two other supporting teams outside the Science Team. These are the Data and Downlink Team (DDT) and the Vehicle and Spacecraft Operations Team (VSOT). All these teams work together to perform the mission. In doing so, their objective is to accomplish the scientific objectives of the mission.

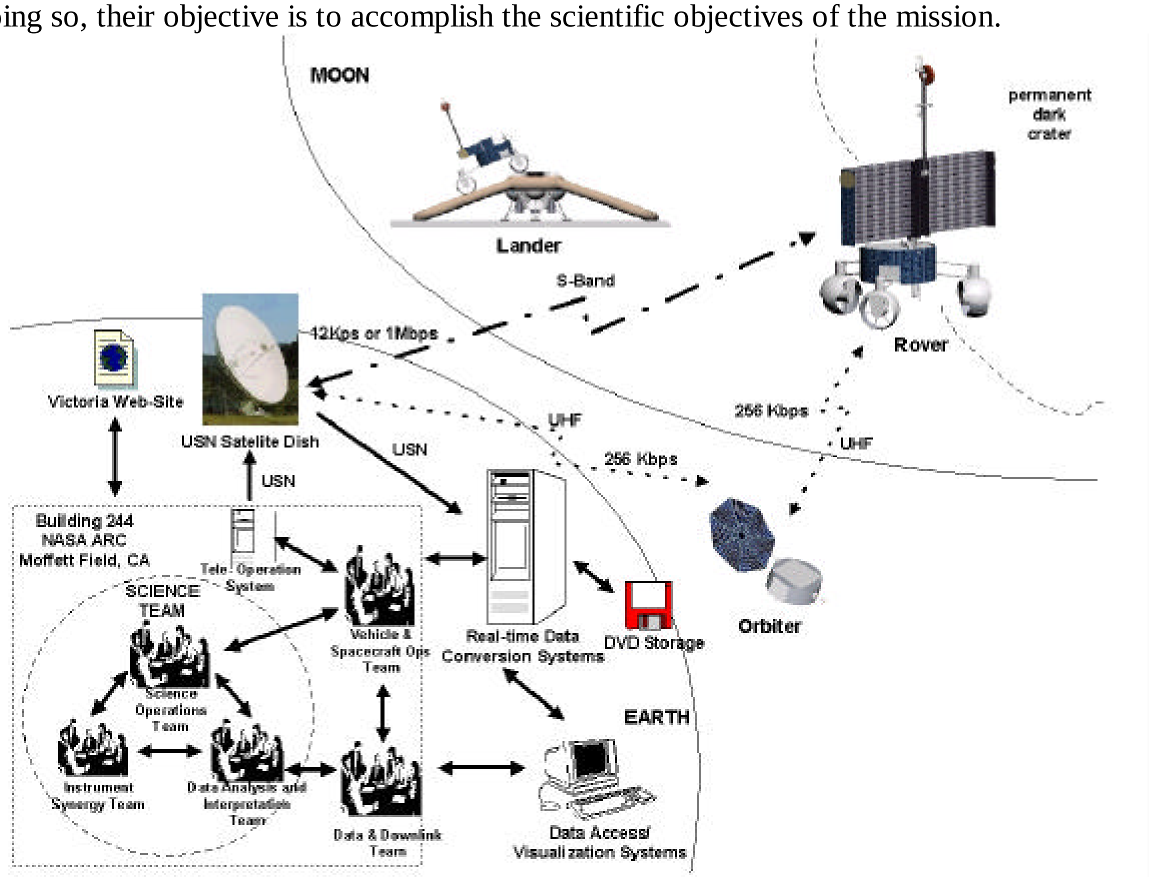

Figure.1. Victoria work system

Rover downlink data will come to NASA Ames via the Universal Space Network (USN) data connection and will be automatically converted in near real-time to accessible data formats that can be made available to the teams via data access and visualization applications. In the next sections we describe the design of this work system through the design of the agent model, the object model, their activity models and the geographical model

Downlink Activity

When the rover detects hydrogen in the ShadowArea1InCraterSN1 location the downlink process starts. What happens during the downlink process is shown in Figure 2. The VictoriaRover creates a data object with a) the current rover location information and b) the hydrogen data. This data object is then communicated to Earth, via the UsnDish1 object. The UsnDish1 object communicates this data to the DataConversionSystem, located at NASA Ames. As can be seen in Figure 2, the DataConversionSystem performs two conversion activities, one for the hydrogen data and one for the location data from the rover. When the VisualizationSystem receives the newly converted data, the system alerts the user, i.e. the DAIT team. This simulates the work practice that a member of the DAIT is monitoring the VisualizationSystem while in the activity "WatchForDownlink". When the DAIT agent detects that there is newly available neutron detector and location data, it retrieves the data from the VisualizationSystem object (i.e. the activities "RetrieveNeutronData", "InterpretNeutronData", and "FindRoverLocationData"). This simulates the DAIT team members looking at and interpreting the rover's neutron and location data, using the visualization system.

Then, the DAIT team communicates their findings to the SOT. The scenario states that the hydrogen data suggest that the rover has found hydrogen in the "ShadowArea1InCraterSn1" area. When the SOT hears these findings, it decides very quickly what the next command sequence for the rover is, and communicates this decision to the VSOT team (i.e. "CommunicateDoDrillActivity" activity).

The communication tells the VSOT team that they have to transmit the command sequence to the VictoriaRover. The command sequence tells the VictoriaRover to start the "SearchForWaterIceInPermanentDarkArea" activity.

Calculating Energy Consumption of Rover

The length of this downlink and second uplink process determines the length of the "Waiting" activity of the VictoriaRover, which simulates the time the rover is waiting for the Victoria science team to decide the next command sequence for the rover (not shown in this paper).

The model calculates the energy consumption for every rover activity during the simulation of the scenario, as is shown in Figure 3. The energy the rover uses during the "Waiting" activity is defined by the energy needed for *Thermal Protection during driving + Command and Data Handling during driving*. What this means is that even while the rover is standing still and "doing nothing," it consumes power for its thermal protection and its commanding and data handling for its subsystems, such as its processor board.

Figure 3 tells us that given the energy used in the scenario—drive 900m into the crater, and take one 1.0cc sample at 10cm depth—with the current work system design, the robot has used almost a third of its power:

EnergyRate(drilling in permanent dark crater) ˜ 0.30

This variable represents the rover power consumption effectiveness of the work system design, and is a measure that can be used to compare different work system designs for a model scenario.

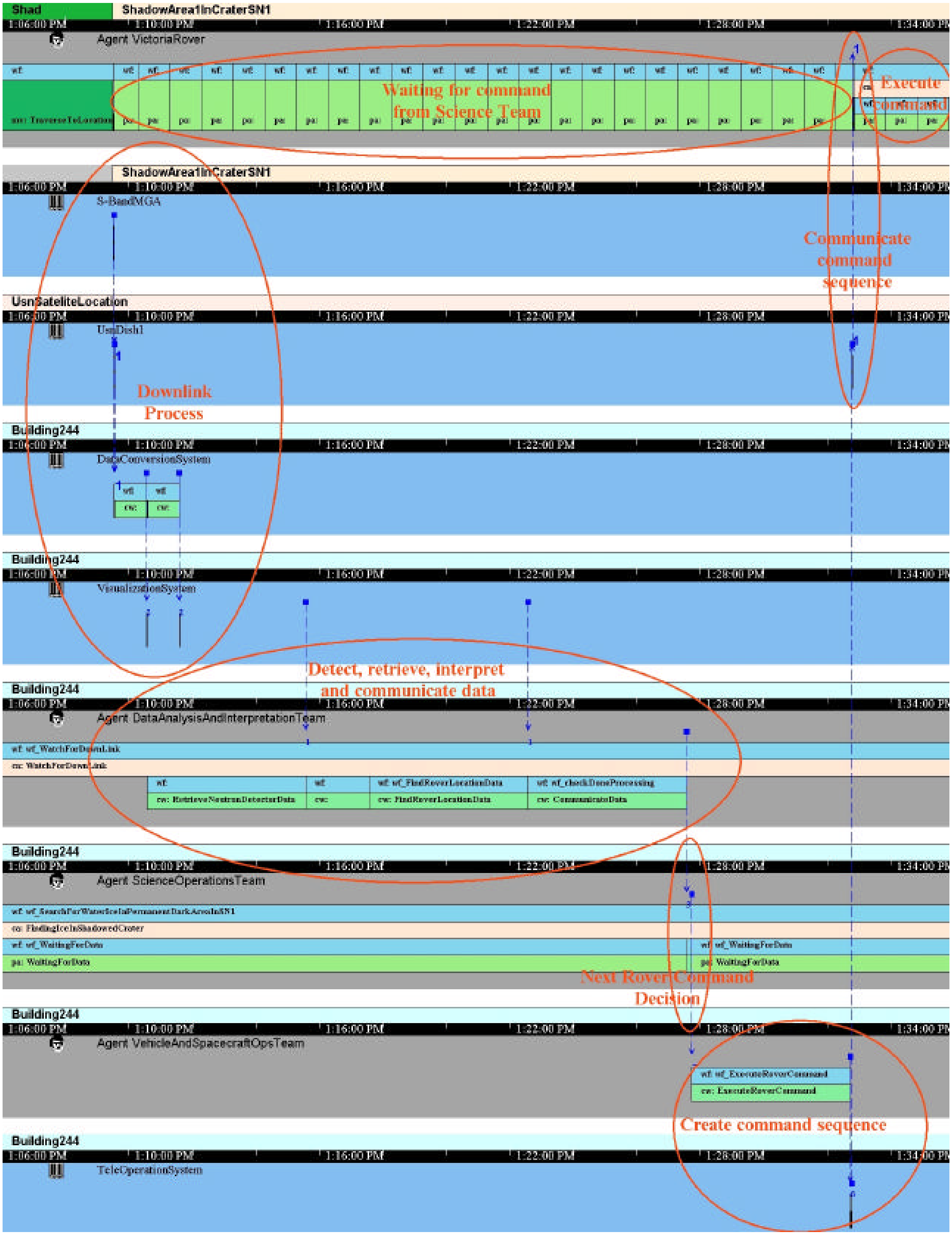

Figure 2. Simulation of downlink and second uplink command activities

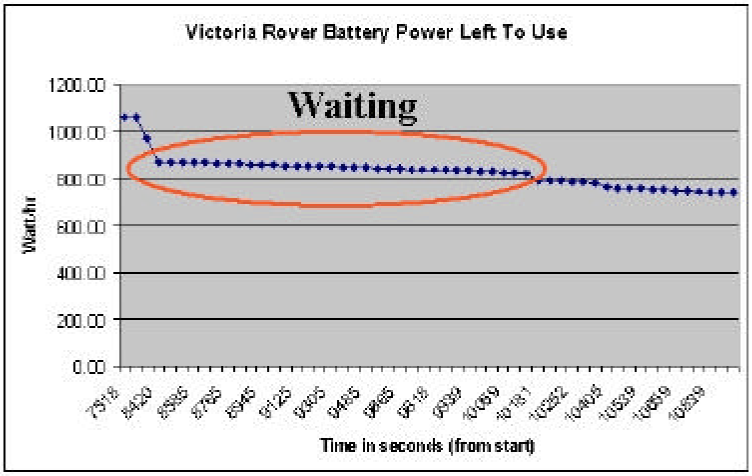

Figure 3. Rover battery power left based on activities

Conclusions

In this paper we described the use of the Brahms multiagent modeling and simulation environment in designing a work systems. We described how Brahms allows modeling at the work practice level, and showed how this methodology was used in a case study to design the mission operations work system for the proposed Victoria mission.

The benefit of using the Brahms approach in modeling a design of a new work system is that it allows for a representation of the behavior, communication and movement of the individual teams, as well as that of the rover and its instruments. This allowed showing the impact of the work process of the Earth-based teams on the energy consumption of the rover in performing a science mission, and thus shows the possible science result given the robot's capability and the work system design. Using the Victoria model will allow mission designers to compare different work system designs before critical mission decision have been implemented.

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Designing Projects: An Evaluation of a Computational Simulation Model in the Context of Small Software Design Projects

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A main interest in the field of project management has traditionally been concerned with the ability to predict the performance of projects. However, as globalized competition and increased customer orientation has increased the concurrency of product development activities, the traditional project management tools like Critical Path Method and Project Evaluation Review Technique fail to deliver reliable estimates of project duration. At the same time developments in computational technology and in organizational theory have provided for more sophisticated project management tools.

One of these new tools is the VDT framework that claims to deliver more accurate predictions of project performance. By using a discrete event simulation model, the VDT framework uses micro contingency theory to predict macro-behavior of design projects. Hereby the VDT model not only includes the increased coordination load imposed by an increased concurrency in the execution of the product development activities in the prediction of project performance, the VDT model also offers the option to predict the performance effects from a change in the project design parameters.

In this paper we analyzed the applicability of the VDT simulation model as a project management tool in the context of small software development projects. To do that, we conducted a theoretical review of project management characteristics for small software development projects. Further, we conducted a case study where we implemented the VDT simulation model in a small software development project and analyzed the applicability of the VDT model in terms of representational capability and usefulness. We then compared the result from the case study to the findings in the theoretical review to make a basis for broader conclusions for the use of the VDT simulation model in small software projects in general.

The findings of the case study revealed that the VDT model had problems representing both the task and the organization of the case project. The problem representing the project task was caused by difficulties identifying the customer requirements associated with the identified project activities. This meant that we could not fully represent the uncertainty and the complexity of the tasks, and therefore we could not fully represent the coordination requirements imposed by the nature of the project task. The main problem representing the organization of the case project was caused by the fact that the positions of the project participants in the project hierarchy were connected to project activities and therefore changed throughout the project lifetime. This dynamic aspect of the project verification structure could not be modeled in the VDT model. Because of this, we could not accurately represent the routing of the exceptions and the decisions in the case project, and therefore we could not fully represent the coordination capacity of the project organization.

For the assessment of the usefulness of the VDT model, we subsequently analyzed the ability of the VDT model to predict project performance and to predict the performance effects from a change in the project design. Because of a poor reporting discipline in the case project, we were not able to collect data to perform an analysis of the ability of the VDT model to predict project duration. Regarding the ability of the VDT model to predict cost, our analysis showed that the VDT model performed worse than the original estimates for the prediction of the cost of the individual project activities, while the VDT model provided considerable better prediction than the original estimate of total project cost. Again, these results must be taken with some precaution due to the poor data foundation. According to the ability of the VDT model to predict project risk, our analysis showed that since we could not fully represent the coordination requirements of the project tasks, we could not predict all the major project risks that occurred in the case project. Finally, our analysis of the ability of the VDT model to predict the performance effects from changes in the project design parameters showed that because of the disability to represent the verification load of the project hierarchy, the VDT predictions did not confirm the predictions from organization theory.

For the assessment of the general applicability of the VDT simulation model in the context of small software development projects, our analysis suggests that since software projects in general can be characterized by ill-defined goals, the VDT model will not be able to include the full coordination load of a software development project. This means that while the VDT model may visualize some important aspects of projects in this context and may identify some project risks it must be used with caution. Due to the many possibilities in setting properties for the objects in the VDT model and the dynamic interaction between some input parameters it is our judgment that users should obtain solid understanding of the theoretical basis for the VDT framework and perform a reasonable number of model studies before making any real-life changes to projects based on VDT models of the project. Even though the VDT framework incorporates the operational uncertainty and therefore makes more reliable predictions it does not and cannot take the contextual uncertainty into account, indicating that the predictions of the VDT framework should be interpreted with caution in contexts with relatively high contextual uncertainty.

In the project management perspective the VDT simulation model's inability to represent the dynamic hierarchy in the case project cannot be generalized for all software projects. As such, not all software projects can be said to have dynamic

hierarchies. We can however conclude that small projects in general will require a high level of decomposition due to a lower degree of specialization, which in turn will tend to amplify the problem of identifying product requirements.

Finally, it is our assessment that although the VDT simulation models shows serious limitations in the representational capability and usefulness in the context of small software development projects, there are still major benefit to be drawn from implementing the VDT framework. These benefits include the detailed insights of the project's characteristics and the identification of interdependencies between project activities and between project actors that are gained during the structured data collection and preparation for the model building.

Hierarchies Vs Markets: Using an Agent-based Marketplace

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The merger of distributed object technology, agent systems and electronic commerce enables a new generation of useful information services. With the advent of interoperable information services, markets featuring software agents as information service/product providers can be created. Meta search engines that rely on a marketplace of search engines and software component marketplaces (e.g., flashline.com) are examples. . The design of these new e-markets requires an understanding – in economic terms – of the interaction between the coordination scheme used to coordinate the agents and the decision strategies used by these agents in market sessions.

Using a stylized marketplace for machine learning services, IBIZA-ML, we present our simulation-based approach to analyze the interaction between two coordination mechanisms – a centralized scheme and a decentralized scheme – and two agent decision-making strategies – random and information intensive strategies. An analytical solution to this research question is intractable. In IBIZA-ML the information products are custom-built -- products are created on demand based on inputs given by the buyer. Brokers and seller-agents in the marketplace are realized using software agents.

A typical market session in IBIZA-ML proceeds as follows. A customer with a dataset for which a predictive model needs to be built submits a request to the broker intermediating a marketplace for predictive model building services. Upon receiving the customer request, the broker initiates a *market-session*. The seller-agents are model-developing agents building predictive models according to the specification given by the customer and are registered with the broker. The quality of the models developed by these seller agents that choose to participate in a market session are evaluated and the seller-agent with the best quality is chosen as the winner. See Arora et al. (1999) for details.

For each market-session, seller-agents are chosen to participate using either a centralized scheme or a decentralized coordination scheme. In a centralized scheme, the broker decides which seller-agents should participate in a market session. In the decentralized scheme, the broker broadcast the request to all seller-agents in the marketplace and the seller-agents decide independently to participate in the market session. In either coordination scheme, the agents performing decision making can either adopt an information intensive decision making strategy or a random decision making strategy.

Note that decisions for each market-session is made ex-ante where there is uncertainty about the quality of the custom-built information product. Also recall that multiple seller-agents may build a product; the buyer accepts only a single information product: the one with the highest quality. The winning seller-agent generates profits while other seller-agents incur a loss.

We compare the performance of these schemes adopting different decision-making strategies using social welfare as the metric. Variables such as the marginal cost of computing, the marginal utility for unit quality point, the percentage of consumer utility paid as price for the model are all treated as exogenous inputs . Details about the set-up are provided in Arora et al. 2000. After simulating about 200 market-sessions, results show that the *information intensive* decision strategies dominate *random* strategies under either coordination scheme. Within information intensive strategies, we find that the centralized and the decentralized mechanisms generate social welfare competitive to each other. Also, we find that the decentralized coordination scheme using parsimonious information and simple decision rule performs well in comparison to the centralized information intensive scheme that internalizes the externalities.

Though the analysis in this paper is limited to social welfare metric, we can extend the analysis to other metrics such as the seller-agent's profit. The results of the analysis can provide a market designer with valuable insights about the impact of the strategies and policies used in the marketplace.

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Beyond Control: Modelling Political Parties as Decentralized,Voluntary Organizations

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Since Downs (1957), spatial models of political parties have depicted parties as unitary rational actors, usually motivated by vote-maximizing goals. In the prototypical example, for instance, two parties compete for the maximum number of votes by "locating" themselves along a left-right ideological spectrum. Under the most common set of assumptions for the two-party model, the party closest to the median voter's ideological preference wins the most votes, and so the two parties converge in equilibrium to the median voter.

In the real world, of course, matters are not so simple. As most lobbyists and political observers will attest, political parties do not behave as unitary actors. The members of a party often have real, nontrivial differences over issue preferences, goals, strategies, and even perceptions. Some may perceive the party to be near the middle, while others see the party as extreme. Some partisans may want to move the party toward the middle of an issue, while others wish to "lead" public opinion, steering the party away from the middle. Unitary actor models of parties typically miss these political differences inside a party, ignoring the considerable collective action problems that must be overcome before such a large and decentralized organization can approximate unified strategic behavior.

In this paper I present a spatial model of party behavior that depicts parties as diffuse, voluntary collectivities of individuals rather than rational unitary actors. The model is a variant of the one used by Tiebout (1956) to describe the provision of local public goods. In Tiebout's system, citizens choose where to reside from among a set of communities, basing their decision on the different bundles of public goods offered by each community. Citizens who care more about one type of good, say public schools, will move to a different community than citizens who care more about other goods, such as public beaches or a senior center. A community's particular bundle of public goods is democratically determined by its citizens, producing a dynamic whereby the movement of citizens between communities produces changes in the bundles of public goods, resulting in additional relocations by citizens, and so on, until an equilibrium is reached.

The model presented here is similar to a standard Tiebout model with important exceptions. Instead of people choosing to reside in communities, voters choose to identify with parties, and rather than making decisions based upon bundles of public goods, citizens evaluate the parties on the parties' issue positions. The parties' positions, on the other hand, take the median of their members' positions on each issue. An example of the dynamic is shown in Figure 1, which diagrams the process for two parties and several hundred voters whose preferences are uniformly distributed over two issues.

The first panel in the figure shows the initial random locations of the party platforms (represented by two black dots), the party identifications of the voters based on the initial platforms (represented by light and dark shadings), and the new party platforms calculated from the median preference on each issue within a party (represented by the large white circles). Each successive panel depicts the next iteration, showing the previous party platforms, the new party identifications based on those platforms, and the new platforms calculated from the latest configuration of voters' identifications. After following a serpentine trajectory, the platforms eventually stabilize at $t = 8$, when the platforms settle at the population's quartiles on one issue and the median on the second issue. At this point, each platform is at the median of its members' preferences on each issue, and no voter can increase her utility by changing parties.

Various innovations to the model – such as different numbers of parties, different distributions of voters' preferences, and a federal system – can be easily incorporated without losing generality or predictive power. The result is a rich model that captures the decentralized nature of modern political parties and explains seemingly irrational party behavior without giving up the virtues of a parsimonious model.

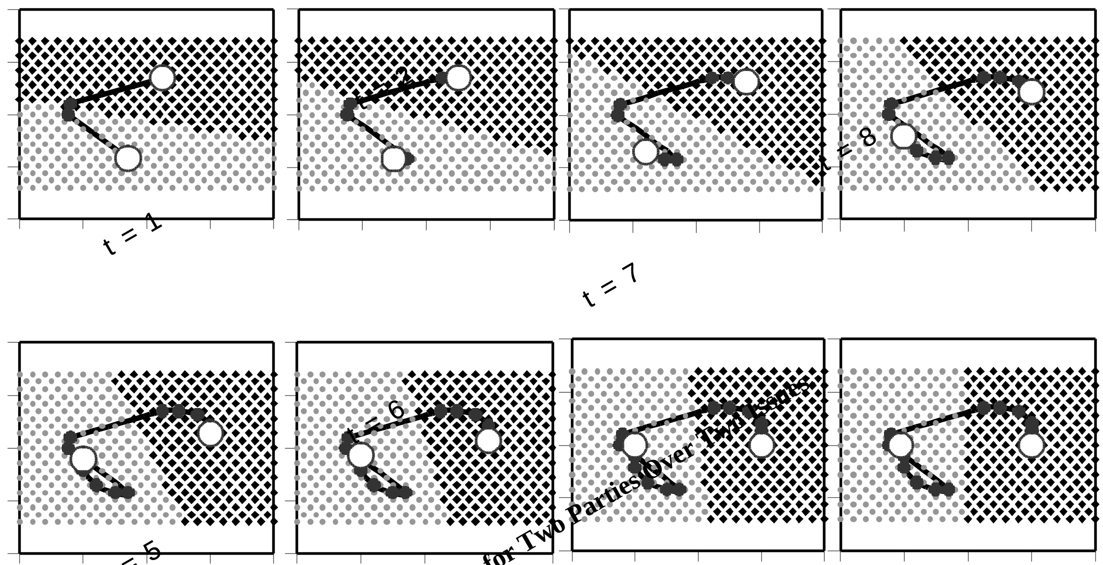

Figure 1. Platform Dynamics for Two Parties Over Two Issues

The Economy of Altruism

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Altruism is generally thought of as behaviors that benefit others at a cost to the altruist. Extreme cases of altruism, in which an individual sacrifices its reproductive potential or its live in order to favor another individual, are common in nature and have been successfully explained in several cases by kin selection theory, providing a basis for Sociobiology. However, kin selection theory does not explain many of the social phenomena that involve some kind of altruistic acts. Thus alternative explanations have invoked mutualisms to explain apparently altruistic acts among social individuals. In most of these analyses, altruism and mutualism have been thought of as beneficial to the species or to the group the altruistic or mutualistic individuals belong. Agent based computer simulations have shown that economic considerations, rather than kinship, are better predictors of social behavior. Specifically the simulations suggest that mutualistic or altruistic acts require the existence of a social synergy (Jaffe 2001) or dynamic effect that provides a greater benefit to the sum of the interacting parts when altruistic or mutualistic acts occur. In many real situations of mutualistic acts, the benefits to the actors are asymmetrical, but not necessarily negative to any of the parties. Jet mutualism and altruism represent but two points in a continuous range of possibilities. Using an agent based computer simulation model and Monte Carlo exploration of variable landscapes, a range of possible situations of conflict between the individual and the group was studied. The results show that no simple situation could be found where altruistic-mutualistic behavior was beneficial the group. In most cases atruistic-mutualistic behavior was detrimental to the groups and in the best of the cases it was neutral, regarding the overall efficiency of the system in accumulating resources (GDP), compared to equivalent systems where no altruistic acts are allowed. The maintenance of altruistic-mutualistic acts depends upon the existence of non-economic factors or on the existence of a synergic effect of the mutualistic interactions.

Methods:

An agent based computer simulation called sociodynamica was used. The model simulates a continuous two-dimensional spherical world in which agents search for resources (R) in order to survive. Each agent acquired a single unit of resource (w_o) each time it encountered a resource, accumulating wealth (w). Agents spend some of its wealth in order to survive, consuming wealth at a basal constant rate (b), which was a fraction of the resource unit. The wealth of each agent changed each time step t :

$dw = -b + w_o$; where $w_o = 0$ if no resources are encountered.

Agents with no resources left ($w = 0$) perished. Agents had movement defined by the distance they displaced themselves in random directions each time step (m) producing a Brownian motion of variable speeds depending on the value of m. Each time an agent met another at a distance smaller than a given contact radius (r), an altruistic act could be triggered depending on the difference in wealth (w_1-w_2) between the two agents and the altruistic threshold (_) of the agent that moved last. If w_1-w_2 > _ (the last moving agent was the wealthier over the threshold _), it transferred wealth to the less wealthy. The amount transferred depended on the generosity (g) of the last moving agent, and was calculated as $(w_1-w_2). g$.

Resources could be either replenished continuously ($R_D = 0$) or were exhausted after consumption ($R_D = 1$); they could be concentrated in a single patch ($R_N = 1$) or in various patches of the same size ($R_N = n$); and the total amount of resources was constant at 100 w_o distributed in n sites forming a square.

The Monte Carlo exploration of variable landscape was performed by randomly assigning values to R_D, R_N, R_S, _, g, m and b; and running the simulation for 40 time steps.

Results

When simulations of the Monte Carlo variation were run, we obtained no situation where altruistic behavior (large values of g and/or low values of _) produced a higher GDP. Only if synergistic mutualistic interaction or secondary benefits for altruistic acts were simulated, could we find variable combinations which produced higher GDP for higher altruism.

Conclusion

Altruistic behavior and/or generosity towards others is not a stable strategy in a pure economic environment

The Threshold Model of Collective Action Revisited

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How to balance individual and collective actions has always been an interesting topic in social sciences. In a society with a well-developed division of labor, collective actions are often called for when the resources needed to accomplish a task exceed one individual party's capacity. However, how to mobilize such an effort remains a challenging issue because public good, as a product of this collective effort, is *non-rival* and *non-excludable*. The *non-rivalrousness* of public good (also referred to as *jointness of supply*) refers to the situation in which one person's use of the good does not diminish the level of provision for the other users (Hardin, 1982). The *impossibility of exclusion* principle argues that all members of the public can enjoy the good even if they do not contribute to it (Barry and Hardin, 1982). Influenced by the basic presumptions of the game theory and neoclassical economic theories, Olson (1965) saw the non-excludability feature of public goods, or the lack of well-defined property rights, as the cause of the paradoxical condition among rational decision-makers. He argued that contribution to collective good would lead people into social traps in which the freedom to pursue immediate individual gains hurts long-term profits both of the group and of individuals. The trap is described as having two jaws, the free rider problem and the efficacy problem (Platt, 1973). On the one hand, due to the principle of non-excludability, members of the group cannot be denied the access to the public goods even though they do not contribute. On the other hand, those who have contributed may not be able to observe the difference made by their contribution, nor garner enough gains from the common resource pools to defy cost. The only solution out of the trap is to use selective incentives to solicit contribution.

Whereas early research on collective actions focuses primarily on the cost and benefit calculations involved in participation (Oliver, 1980; Oliver, Marwell and Prahl, 1985; Olson, 1965), recent research on this subject has witnessed a shift of attention from pure economic concerns to approaches that are more inclusive of the impact of social factors (Fulk, Flanagin, Kalman, Monge and Ryan, 1996; Granovetter, 1978; Hollingshead, Fulk and Monge, forthcoming; Macy, 1990, 1991, 1995; Marwell and Oliver, 1993; Monge, Fulk, Kalman Flanagin, Parnassa and Rumsey. 1998). One of the major themes of this sociological turn in the research orientation is to study how social ties may influence individual decision-makings (Granovetter, 1978; Marwell, Oliver and Prahl, 1988; Monge, Fulk, Kalman Flanagin, Parnassa and Rumsey. 1998). The incorporation of the structural analyses of network relationships can be extremely useful in the study of collective action because it offers a powerful alternative to break through the social traps deemed as irrevocable in the rational choice models.

Granovetter's threshold model (1978) is one of the first endeavors along this line of research. He argues that each individual person in the pubic is endowed with different levels of threshold of participation. Whether s/he will participate in a collective action, e.g. a riot, or adopt a new innovation depends on the level of impact that s/he receives from her/his social networks. In conceptualization, Granovetter's model marks a significant breakthrough from those pure economic models. However, in testing his propositions, his simulation falls short of providing adequate support on how the density of network ties may actually impact the chaining processes of collective action. Macy revisited Granovettor's model in 1991 and found that the assumption of fixed threshold is not realistic. Building on his previous research on the adaptability of human behavior, Macy has designed a new model that allows people's threshold to change over time in response to their learning experiences. He also reports that strong and weak ties can have different impacts on the realization of the good. However, from the equations provided in the paper, it is not clear how social ties can have an impact whatsoever because none of the parameters in the equations measure relationships. Another effort to extend Granovetter's original model comes from Abrahamson and Rosenkopf (1997). In their model they study how social ties may trigger bandwagon effect in collective action, but they concentrate only on direct ties.

In this paper, I propose an agent-based model to study how social ties, both direct and indirect ones, can impact a person's participatory decision making. The current model is developed on the basis of Macy's (1991) revision of Granovetter's threshold model. Despite its limitations, Macy's model remains one of the most comprehensive research endeavors on this topic. It is modified to include network relationships as one of the major parameters that determine the likelihood of contribution. Simulations are then run to test the robustness of the threshold model under different types of conditions, including different levels of the jointness of supply of the good, and the levels of correlation between individual resource and interests. But primarily the research attention is on the distribution of threshold and network density because these are the variables that are central to the threshold model. The results show that the provision level of the public good is highest when interests and resource have a high positive relationship, and the provision level is highest when the threshold follows a uniform distribution. Overall network density also has a positive effect on the realization of the good in the threshold model of collective action. If the threshold follows a normal distribution, the difference between high and low density condition is most obvious when interest and resource have a high positive relationship. If the threshold follows a uniform distribution, the difference between the high and low-density condition is most obvious when interest and resource have a high negative relationship. Further experiments are needed to explore why this is happening. And the paper ends with a discussion of possible future extensions of using computational models to study collective actions.

Modeling Structure and Cognition in Organizations: A Meta-Network Computational Approach

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Introduction

In this paper we present a meta-network approach to modeling organizations in terms of three basic domain elements: cognitive agents, tasks and resources (Krackhardt and Carley, 1998). Building on mainstream social network and distributed artificial intelligence literature, we propose that formalizing dependencies between domain elements at various levels provides a rich grammar for theorizing about organizations (Wasserman and Faust, 1994; Wooldridge, 2000). We demonstrate the versatility and utility of this approach for generating a series of testable hypotheses about organizational processes and performance. These hypotheses are tested through a series of agent-based social simulations. It is shown that both structure and agents' cognition are important predictors of how an organization works, and what results it achieves. In turn, the predictive power of structure and cognition depends on the generation of group mind-like forms of mental models emerging from a network of socially and cognitively integrated agents.

The Model

We describe organizations along four levels:

The socio-technical level. This level refers to the basic structural networks underpinning the organization (Wasserman and Faust, 1994). It shows who is connected to whom ("social network"), who controls what resource ("assignment network"), who can perform what task ("capabilities network"), what resource can be substituted for which ("substitution network"), what resource is needed to perform what task ("requirement network"), and what task needs to be performed before which ("precedence network") (Table 1).

Table 1. The Individual Socio-Structural Level

	Agents	Resources	Tasks
Agents	Social Network	Assignment Network	Capabilities Network
Resources		Substitution Network	Requirement Network
Tasks			Precedence Network

The individual cognitive level. This level refers to the individual agents' mental states (Wooldridge, 2000). It indicates who has what belief ("knowledge network"), who has what goal/intention/commitment ("motivational network"), what information is needed to use what resource ("skills network"), what resource is needed to fulfil what goal/intention/commitment ("assets network"), what information is needed to perform what task ("needs network"), and what task needs to be performed to fulfil what goal/intention/commitment ("strategy network") (Table 2).

Table 2. The Individual Cognitive Level

	Beliefs	Goals/Intentions/Commitments
Agents	Knowledge Network	Motivational Network
Resources	Skills Network	Assets Network
Tasks	Needs Network	Strategy Network

The synthetic socio-structural level. This level refers to how agents, resources and tasks are actually organized and coordinated within the organization (Krackhardt and Carley, 1998). It reveals who interacts with whom ("coordination network"), who uses what resource ("capital network"), and who performs what task ("organizational network") (Table 3).

Table 3. The Synthetic Socio-Structural Level

	Agents	**Resources**	Tasks
Agents	Coordination Network	Capital Network	Organizational Network

The synthetic cognitive level. This level refers to the higher-order forms of joint cognition that emerge within the organization from the interplay of the individual agents' mental attitudes (Wegner, 1987; Wooldridge, 2000). It reveals what joint doxastic attitudes emerge from individual agents' beliefs, what joint conative attitudes emerge from individual agents' goals and intentions, and what joint deontic attitudes emerge from individual agents' commitments (Table 4).

Table 4. The Synthetic Cognitive Level

Agents' Mental Attitudes (Individual Level)	**Organization's Shared Mental Models (Synthetic Level)**
Beliefs	Doxastic Joint Mental Attitudes (consensus; culture; mutual beliefs; organizational transactive memory; agreement; etc)
Goals/Intentions	Conative Joint Mental Attitudes (joint goals; joint intentions)
Commitments	Deontic Joint Mental Attitudes (organizational commitments)

The four levels are a set of increasingly inclusive models. The sequencing along the four levels indicates what sorts of social behavior and cognitive representations arise at various stages of abstractions and how to proceed to create a more adequate conceptualization of the organization. Based on their structural connections, the information they hold, the states of the world they want to achieve, the resources they own and the tasks they can perform, the agents interact with one another, communicate, and allocate resources and tasks among themselves. In turn, interaction and coordination enable the agents' mental states to combine and generate joint forms of mental attitudes (Wooldridge, 2000). These, ultimately, represent the cognitive ingredients of the joint processes undertaken by the organization, and therefore impact upon performance and how effectively the organization evolves over time.

Hypotheses

One of the insights that this model can bring is to derive some sophisticated analytical formalizations of the patterns of interaction between structure and cognition in organizations, both at the individual and the joint level, and how this interaction impacts upon organizational processes and performance. First, some hypotheses can be derived with respect to the influence that the individual socio-structural level has on the synthetic levels:

Hypothesis 1. Higher degrees of the structural connectivity of the social network help to generate more accurate and effective coordination/capital/organizational networks, and this, in turn, helps to combine the mental states of the agents into stronger joint mental attitudes.

Hypothesis 2. The higher the degree of environmental capacity (i.e., availability of resources and their heterogeneity), the lower the degree of environmental complexity (i.e., concentration among resources), and the lower the degree of environmental uncertainty (i.e. how predictable tasks are over time), the more accurate and effective the coordination/capital/organizational networks, and the stronger the organization's joint mental attitudes.

Second, some hypotheses can be formulated in terms of the impact that the individual cognitive level has upon the synthetic levels:

Hypothesis 3. Agents' cognitive accuracy helps to improve the accuracy and effectiveness of the coordination/capital/organizational networks, and paves the way for stronger joint mental attitudes.

Hypothesis 4. Structural connectivity and agents' cognitive accuracy are mutually reinforcing in generating stronger joint mental attitudes and more accurate and effective coordination/capital/organizational networks.

Finally, the model allows some hypotheses to be derived with respect to the impact that the synthetic levels have upon organizational processes and performance:

Hypothesis 6. The stronger the organization's joint mental attitudes the more effective and efficient the organizational processes.

Hypothesis 7. The synthetic socio-structural and cognitive levels are mutually reinforcing in generating more effective and efficient organizational processes.

Preliminary Results

Agent-based computational analysis is used to test these hypotheses. In particular, a number of virtual experiments are undertaken to examine the impact that social structure and agents' cognition have upon the effectiveness and efficiency of organisational decision-making. In these experiments, the number of agents, their relations, their cognitive accuracy, the resources they control, and the tasks they are able to perform are allowed to vary. Organizational performance is measured in terms of how close the actual joint decision is to the organization's aspiration level (effectiveness), and how many messages it takes the agents to reach a joint decision (efficiency). Initial results of a first set of experiments show that the higher the number of interactions in which each agent is involved (connectivity), the less it takes for a joint mental attitude to be generated, and the higher performance is. Thus, one way to make the mental states of the agents of an organization converge and generate a joint mental state is to enable the agents to increase their interactions in such a way that each other's mental states can be mutually affected. Also, even though efficiency is negatively correlated with the number of the interacting agents (as more agents need to send more messages to one another), nonetheless as more agents become involved, effectiveness is enhanced by the fact that new agents provide new resources and abilities to bring about the expected results.

A second set of experiments reveals that, given the individual socio-structural level, the higher the degree of the agents' cognitive accuracy, the more accurate and effective the networks at the synthetic socio-structural level, and the higher the organization's performance. In fact, when agents have more accurate beliefs (either introspective or about each other), they can organize work more sensibly, assigning tasks to the members who will perform them best with the most appropriate resources. Coordination improves as well, because agents can identify and choose whom to interact with in order to have their goals fulfilled. As a result, agents can work more efficiently, develop stronger forms of shared cognition more quickly and, ultimately, improve organisational performance. The upshot is, therefore, that the impact that structure has on performance depends on how accurate agents' cognition is: for example, the beneficial effects of a more connected social network upon performance become weaker as the agents' cognitive representations become less accurate.

Finally, in a third set of experiments, the potential benefits of differing types of joint mental attitudes for organizational performance are tested. When agents are allowed to communicate more information about each other, they gradually develop higher degrees of awareness of each other's beliefs, goals, intentions and commitments. This, in turn, enables their mental states to combine into stronger forms of joint mental attitudes. As these attitudes approach their strongest form, joint commitment, the agents learn how to anticipate, rather than simply react to each other's behaviour, how to use each other as memory aids and, ultimately, how to rely upon each other to get their job done (Wegner, 1987). This, in turn, by affecting the ways in which agents interact with one another, and how resources and tasks are organized (synthetic socio-structural level), turns out to be beneficial for the organization's performance, thus allowing the agents to make a joint decision nearer to their aspiration level.

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Leveraged Diffusion

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Diffusion is a broad topic. Innovations diffuse within a business sector. New products diffuse into a marketplace. Change diffuses throughout an organization. In each case, however, diffusion happens as people adopt a new idea, whether that idea be physical or conceptual. That is, diffusion is inherently an ideational process.

Much of the literature on diffusion focuses on the descriptive shape of the curve that describes the rate and extent of adoption within a defined population. What we would like to propose is a normative model, one that suggests a strategy for how to more rapidly change the rate of adoption in the population. Specifically, we propose a model that makes some reasonable and simple assumptions about the diffusion process and the implications of which allow the proponents of the new idea to leverage their investment of time and effort in substantial ways.

The assumptions of this model state simply:

If an individual *i* tries a new product, that individual has a probability α of adopting the product. All individuals within the population have the same value of α.

If a friend *j* of an individual *i* adopts a new product, then individual *i* has a probability β of trying the new product. All individuals within the population have the same value of β.

With these two simple assumptions, we can describe a process by which the process of diffusion is enhanced, or leveraged, such that an investment in diffusing a new product garners higher return through higher adoption/consumption rates. First, we describe a base line procedure of diffusion through random sampling of people within a prescribed population. These randomly selected people are the seeds, in whom we invest (by, for example, providing them with a free sample of the product we wish them to adopt). These seeds and their friends adopt the product at a rate given by parameters _ and _. We then compare this procedure to a simple alternative: Instead of investing the free product in the hands of the randomly selected seeds, give the product to one randomly selected friend of each of the seeds. This simple alternative, one we call the leveraged procedure or strategy, is shown to have two properties:

1) The leveraged strategy always performs at least as well and almost always better, on the average, than the randomly selected seed procedure. This is true independent of the number or structure of friendships within the population.

2) The extent to which the leveraged strategy does better (i.e., the payoff for using the leveraged strategy) can be estimated in any population by taking a random sample of friendship ties within the population. That is, it is not necessary to know the entire structure of the population of friendships to know the expected payoff for the leveraged strategy.

We provide formal proofs of each of these properties. In addition, we demonstrate through examples how the leveraged strategies can be applied to general diffusion processes.

MODELING INFORMATION GROWTH AND DIFFUSION AS A FUNCTION OF NETWORK STRUCTURE

MARSHALL VAN ALTSYNE

Information Seeking in Social Context: Personal and Impersonal Sources Employed in Intentional Search

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Research in the information processing and social network traditions has consistently demonstrated that people rely heavily on other people for informational purposes. For example, evidence accumulating over the past 30 years has demonstrated the importance of relationships for acquisition of information (Granovetter, 1973; Allen, 1977; Burt, 1992; Rogers, 1995), learning how to do one's work (Lave & Wenger, 1991; Brown & Duguid, 1991; Orr, 1996) and collectively solving cognitively complex tasks (Weick & Roberts, 1993; Hutchins, 1995; Moreland, Argote, Krishnan, 1996). Yet despite the centrality of social interaction as a vehicle for knowledge creation, we know little about specific informational benefits people obtain when seeking information from other people.[4] While providing the analytic means with which to model knowledge creation and sharing amongst people, a review of the social network literature reveals limitations to the way in which researchers have traditionally assessed "advice" or "information" seeking networks (see Monge & Contractor, 2000 for a review). Research in this realm has largely proceeded structurally on the role of weak or bridging ties in the acquisition of non-redundant information (e.g., Granovetter, 1973; Burt, 1992; Rogers, 1995).

Recently Cross (2000) conducted in-depth interviews with 40 managers to understand informational benefits that accrue when information is sought from another person. Five informational benefits were reported in this work: 1) solutions (specific information or answers that address questions or problems); 2) meta-knowledge (pointers to databases or other people); 3) problem reformulation (interactions that lead people to think differently about their problem); 4) validation of plans or solutions and 5) legitimation from contact with a respected person. However, this work did not consider people's informational environments holistically to understand what information seekers might get from impersonal sources such as databases, paper archives or the Internet. Further, for information that is obtained through one's network, this research did not explicate formal and cognitive/affective aspects of relationships that impact whom is sought out. The current study was undertaken to extend Cross (2000) work by empirically assessing: 1) the extent to which people derive the five informational benefits from personal as well as impersonal sources and 2) characteristics of the source and relationship between the source and seeker that predict receipt of the five informational benefits.

Research was conducted within the business consulting practice of one of the Big Five accounting firms. Surveys were administered in three offices within the consulting organization. In each case, a stratified sample was collected to ensure equal representation across the staff consultant, senior consultant and manager levels to test for differences in information seeking by virtue of hierarchical position. Surveys were designed to determine informational benefits received from other people as well as characteristics of people sought out and the relationship between the two parties. A standard two step name generator/interpreter methodology was employed to elicit and then define people that the respondents relied on for informational purposes.

The first purpose of this research was to assess the extent to which people derived the five informational benefits identified in Cross (2000) from people in comparison to alternative impersonal sources. MANOVA, ANOVA and paired comparisons were conducted to assess differences in information seeking behavior from six sources of information: 1) people; 2) the global knowledge management database; 3) local knowledge management databases in each office; 4) personal computer archives; 5) the Internet and 6) paper archives. Results indicated that people were consistently considered more important than impersonal sources for all five informational benefits. Thus despite advancements in distributed technologies, search functionality and the Internet, to name a few, this research suggests that people still matter. And it bears noting that this was found in an organization considered an industry exemplar for its knowledge management infrastructure.

As information was heavily derived from other people, a second focus of this research lay with understanding characteristics of the person sought out and the relationship between the seeker and source of information. Three categories of variables were of interest: 1) perceived source knowledge; 2) relationships established by position in organizational structure; 3) informal relationships established by repeated interaction. Control variables proved to be minimally significant in predicting receipt of the five informational benefits. In contrast, inclusion of the perceived expertise of the source was highly significant and generally an important variable in predicting who was sought out for the five informational benefits. All models were significant with variance accounted for ranging from a high of .184 for solutions to a low of .055 for problem reformulation.

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[4] Work in transactive memory and distributed cognition has begun to provide purchase on this by exploring the existence and performance implications of distributed knowledge systems. However, such work has paid less attention to the ways that seeking information from other people facilitates the creation of knowledge. While the situated learning literature has richly demonstrated the importance of relationships for learning at work, such rich ethnographic accounts have also not provided specificity regarding information seeking that could inform modeling of learning in social networks.

Characteristics of the relationship between the information seeker and source also had an affect on who was sought out for the five informational benefits. Variance accounted for with inclusion of relationships established by formal structure ranged from .231 for solutions to .094 for problem reformulation, a significant increase for each of the five informational benefits as indicated by F-tests assessing the increase in variance accounted for with inclusion of these variables (p. < .001). Two findings were significant for relationships established by formal structure. First, boundary spanning did not seem to play a critical role in the acquisition of solutions or meta-knowledge. In contrast, boundaries did seem to matter for whom is sought out for problem reformulation and validation as evident in respondent's tendencies to turn to those within their own group for these informational benefits. Second, relative hierarchical position had an affect on information seeking but this was largely constrained to solutions and meta-knowledge. Post survey interviews suggest that people higher in the hierarchy interact in different face to face and virtual forums than those lower in the hierarchy and these interactions provide them with access to information not available to those lower in the hierarchy.

Finally, relationships established by frequency of interaction or affect were entered. F-tests assessing the increase in variance accounted for with inclusion of these variables were significant for four of the five informational benefits (p. < .001). These relational characteristics did not significantly improve predictive ability of those sought out for legitimation. In contrast, the predictive ability of the model for problem reformulation showed a marked increase with variance accounted for increasing from .094 to .249. Weak ties were important for receipt of solutions presumably as a product of being able to provide reach into networks containing non-redundant information (e.g., Granovetter, 1973; Burt, 1992). In contrast, strong ties mattered for receipt of problem reformulation and validation. For forms of information that require engagement to establish common understanding of a problem domain or transfer of complex knowledge strong ties were important.

In addition to tie strength, we also found willingness of the person sought out to actively engage in problem solving predictive of who is sought out for meta-knowledge, problem reformulation and validation. Again in contribution to traditional theorizing on weak tie relationships, it seems that willingness of a person to actively think *with* the seeker rather than just provide non-redundant information is important to one's ability to assimilate and use new information when a problem is not well defined. Recent discussions of knowledge transfer have fingered the limited 'absorptive capacity' of the recipient as a block (e.g., Szulanski, 1996; Simonin, 1999). These findings suggest a more elaborate understanding of relationships. Individual and collective learning is affected in part by existing knowledge embedded within a group but also on relational characteristics that affect one's ability to understand another person's knowledge.

In general, this research (and results supporting more detailed hypotheses reported in the full paper) indicate that people are highly important sources of information and that both formal and informal dimensions of relationships impact who is sought out for these informational benefits. Of course this study has limitations that should be noted. First, the study was conducted within one organization which limits generalizability. Second, the work is also incomplete in the sense that I did not account for firm-wide variables such as climate. Finally, the study is limited by its focus on positive relationships. Nevertheless, we feel this research makes a contribution to both the information processing and social network literatures. In contrast to the information processing literature's focus on comprehension of objective information, results show that when information is sought from people, benefits beyond objective information accrue that are important to both generating a solution and introducing the solution into diverse social contexts. In contribution to the social network literature, results show that there are several components to the information-seeking network that are affected by social dimensions of a relationship. We hope that future research will explore implications of these findings in relation to social capital, computer-mediated communication and organizational learning.

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MODELING KNOWLEDGE SHARING IN VIRTUAL ORGANIZATIONS

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As organizations continue to disperse geographically, groups interacting through a computer-mediated communication (CMC) medium are becoming pervasive, thereby increasing the number of tasks performed in that environment. A review of the literature on CMC shows that CMC affects the amount and the specificity of the information shared among the group's members, as well as other variables related to group processes. This raises several important questions relevant to virtual organizations: How do they share best practices and knowledge in general? How do they perform relative to co-located organizations? How does personnel turnover affect them? How do they adapt to environmental changes or technological crisis? This study presents a simulation model to examine how different characteristics of the communication technology (CT) affects the organization's ability to share knowledge and to perform its tasks when members are geographically distributed. The main contribution of the model proposed here is the integration of a model of communication technology (see Table 1) with commonly used individual's interaction, learning, organizational design and task models.

This model extends the work by Cataldo and Carley (2000)[5] in four different areas. First, each individual has a probability of interacting with another, denoted $P_{ij}(t)$. This probability is a function of both how much knowledge *i* shares with *j* at time t, denoted $SK_{ij}(t)$, and how many opportunities *i* has to contact *j* relative to *i*'s shared knowledge and contact opportunities with everyone else, denoted OC_{ij}. The introduction of the CT as well as the geographical location of the organizational members will affect the opportunities of contact of each member. Therefore, the original model was extended to make OC_{ij} a function of organizational structure, task interdependence, physical location of the members, individuals' previous knowledge about who knows what, and availability of CT.

Second, the addition of CT also requires a modification to the information exchange modeled in Cataldo and Carley's work (2000). Originally, pairs of individuals were selected and an individual could not be in two or more pairs simultaneously. This restriction works properly for face-to-face communication, however, it does not when using certain kinds of CT such as email. Consequently, the model proposed here extends the original pair-generation algorithm by also considering the degree of ubiquitousness as well as multicasting functionality of the CT.

Third, the original representation of knowledge was extended along two dimensions. First, a basic transactive memory mechanism was implemented. Individuals associate the person from which they learned a particular piece of information with a quality coefficient that represents the likelihood that the information is correct. This coefficient is updated based on an exponentially decreasing function, consequently, incorrect information has a stronger effect on the likelihood of having future interactions with the particular sender. Second, individuals have limitations in their abilities to remember pieces of information. The model implements forgetting by associating a coefficient _ and by assigning a *forgetting policy* to each individual. The coefficient _ represents the likelihood of the individual to forget while the *forgetting policy* refers to which pieces of information are more likely to be forgotten. There are two different policies: first-in-first-out and least-recently-used.

Finally, turnover occurs under three different situations. First, members might be transferred between groups. Second, members might be transferred to different geographical locations. And third, turnover might occur when individuals leave the organization. The model provides different alternatives regarding the selection of the individuals that will be transferred or will leave the organization as well as the characteristics of the new individuals. In the simplest case, an individual from the donor group and an individual from the recipient group randomly selected. A new individual immediately joins the donor group. In addition, the selection criteria could be based on level of experience or position in the group structure. For instance, we could have turnover cases in which managers are replaced with novice individuals.

This model is being evaluated in two stages. First, we performed a preliminary virtual experiment[6]. The results show a significant effect of geographical location. The more disperse the organizational member are, the lower the amount of new task knowledge shared among them. On the contrary, task interdependence affects positively the amount of knowledge shared. The more interdependent the organizational members are of each other the more knowledge they share. In addition,

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[5] Cataldo, M. and Carley, K. M. (2000). Factors Affecting Knowledge Transfer within Organizations: A Simulation Study. Submitted to Management Science.

[6] Considering organizational structure, task interdependence, geographical location, turnover, selection scheme, knowledge representation, and communication technology, this virtual experiment presents a 2 X 3 X 3 X 4 X 2 X 2 X 2 X 3 factorial design. Three different levels of geographical distribution were simulated: all co-located, three geographical locations, and each individual in a different location. In addition, three different levels of task interdependence were examined. Finally, three different mechanisms of communication were simulated: face-to-face interaction, email messaging, and video conferencing. The CTs were assumed to be available to all individuals.

the type of the communication mechanism has a strong statistical effect on the amount of total new task knowledge transferred. The inability of the members to interact effectively affects not only the amount of new knowledge learned but also it is exemplified by the dramatic decrease in performance, in particular, when using email. As individuals interact through email or video-conference, the intrinsic limitations in those mediums reduce the likelihood that the individuals will interact again in the future, therefore, the interaction is confined to the co-located sub-group, restricting the possibilities for learning. This may occur due to different reasons. First, the message might be misinterpreted. Second, the message might contain the incorrect information. Third, the response to a message might arrive too late. When any of these situations occur, the individual will decrease its likelihood of interacting with the sender of those messages. Consequently, the probabilities of interaction decrease almost to the point of isolation.

Finally, the data show an interesting result. There is a significant interaction effect between turnover and transactive memory. In the context of this model, transactive memory refers to the cognitive map created by the individuals about who know what. When the level of transferring people among locations is low, having transitive memory has a marginal negative effect. However, when turnover is high, the "who knows what" cognitive map has a significant negative effect on performance. These results suggest that individuals misuse their time trying to interact with organizational members that do not belong to the organization anymore. An alternative explanation could be that individuals rely on interactions with individuals whose knowledge is detrimental or not useful in the new context, consequently, performance decreases. In addition, the high turnover rate, might be limiting the individuals ability to recognize that problem and adapt.

The second part of this study focuses of modeling the IT group of an Internet-based company. This organization has the IT group distributed in six different locations within four different countries. We finalized collecting the data that will be used in a second virtual experiment to further evaluate the proposed model.

TABLE 1: Communication Technology Attributes

Communication Attributes	Definition
Unicasting	Ability to perform communication 1 to 1
Multicasting	Ability to perform communication 1 to many
Initiation	Ability to initiate interaction
Ubiquitousness	Degree of availability of the medium
Latency	Time elapsed from initiation of the transmission of the message until the initiation of the reception of message
Responsiveness	Time elapsed to respond the message. The total time from transmission of a message to the reception of the reply is equal to "2*Latency+Responsiveness". Responsiveness is a function of three components: availability of the medium, content of the message (e.g. "T: Do you want to go to the cinema. R: Yes/No" or "T: Send me this month's production figures. R: —needs time to perform the task—"), and social factors (e.g. "msg from my manager" or "msg from unknow person", that is status, power, influence, etc.)
Medium Continuity	Functional ability to maintain the thread of conversation
Cognitive Continuity	Cognitive ability to maintain the thread of conversation
Storage & Retrieval Attributes	**Definition**
Storage	Ability to store data
Retrieval	Ability to access a particular piece of data
Searching	Effectiveness of the search mechanisms provided by the system
Manipulation	Effectiveness of the data presentation mechanisms provided by the system
Presentation	Effectiveness of the data presentation mechanisms provided by the system
Ubiquitousness	Degree of availability of the set of functionalities defined as α*Storage + β*Retrieval + δ*Searching + η*Manipulation + ϕ*Presentation, where: $\alpha+\beta+\delta+\eta+\phi=1$
Group-Specific Attributes	**Definition**
Awareness	Ability to provide remote user's context information
Document Versioning	Ability to manage a multiple documents-multiple users environment
Task Progress	Ability to provide task-tracking information to users

Tradeoffs Between Performance and Adaptivity for Organizational Architectures

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Organizational architectures can be characterized by personnel, resources, and tasks and the set of relationships linking them. Previous work has demonstrated that it is possible, using this representation, to design architectures for command and control that meet various performance criteria [Levchuk, Pattipati & Kleinman, 1997]. Some of the performance criteria include communication silence, uniform distribution of workload, accuracy and timeliness in response. Studies of the way in which these organizational architectures adapt have also been done. These studies indicate, among other things, that adaptation is frequent, that not all change is adaptive, and that redundancy (in personnel or resources) eases the ability of units to adapt. This paper examines the link between adaptation and performance. We ask is it possible to design for both high adaptation and performance.

Motivation for this study was based on results of the COMCARGRU study, as part of Bridge to Global, 1999. The analysis is carried out using simulation analysis conducted with the ORGAHEAD [Carley & Svoboda, 1996] and ORGMEM models. The models examine both performance and adaptability of organizational architectures under external change processes and internal communication and resource flows.

PCANSS Representation of Organizational Architectures

The organizational architectures in the computational models and in the actual war game are represented using the PCANSS formalism [Carley & Krackhardt, 1999]. Using the PCANSS formalism we mathematically represent the organizational architecture as a set of matrices linking personnel, resources, and tasks. The 6 matrices are: precedence (TxT), capabilities (PxR), assignments (PxT), networks (PxP), needs (RxT), and substitutes (RxR). For each of these matrices, measures of the organizational architecture exist – such as span of control and complexity. These measures can be divided into three categories — standard network, multi-color, and multi-link. Standard network measures are calculated on matrices where the rows and columns are the same entity such as precedence, networks, and substitutes. An example is complexity. Multi-color measures are calculated on matrices where the row and column entities differ such as capabilities, assignments, and needs. An example is workload. Finally, multi-link measures are calculated using data from two or more of these matrices and so two or more types of relations. Examples aer cognitive load, another is task-congruence.

Previous work indicated that of the set of commonly used measures, both multi-color and multi-link had more power in predicting both performance and adaptability than did standard network measures [Carley, Ren &Krackhardt, 2000]. This suggests that no one aspect of the ORGANIZATIONAL architecture dominates and instead all aspects interact in a complex adaptive fashion to effect a well tuned architecture. In this paper we use these measures to explore whether there is a tradeoff between performance and adaptability.

Factors Affecting Performance and Adaptability

We use a set of 19 measures which cover the set of sub-matrices in the PCANSS matrix and include standard network, multi-color, and multi-link measures. These measures include, Size, Density (complexity), Redundancy, Task Load, Need for Negotiation, and Cognitive Load. As outcomes and intermediate variables we measure performance (task accuracy), adaptability, common operational picture, and sustainability.

Virtual Experiment

In order to examine the tradeoff we conducted a virtual experiment. Using random network generation techniques a set of initial organizational architectures were created. Each structure represents the initial architecture of a different unit. Then these units are "evolved." Multiple simulation engines are used to evolve these structures and so create different possible change paths under different scenarios of what the future might bring. One of these engines is ORGAHEAD [Carley & Svoboda, 1996]. The other is ORGMEM [Carley, Ren &Krackhardt, 2000]. These simulation engines were used to do a series of "what if" analysis, answering the question "what if 'x' happened, then how is the team likely to change it's organizational architecture?". The scenarios examined differ in the "x" that is happening. These scenarios include: downsizing due to attrition, increased workload, and natural change due to individual learning. For each unit, for each change path, the set of measures are then calculated.

Adaptability or Performance

Results indicate that it is difficult to design for both high performance and adaptability. Different factors lead to adaptation and to high performance. As can be seen in Figure 1, multi-color and multi-link measures have the most predictive power, even when multiple factors are taken into account. In figure 1 the dotted lines indicate a negative relation, and the solid lines a positive relation. As can be see, while high cognitive load degrades performance it actually enhances adaptability. Additional analyses examine the level of congruence associated with well performing and adaptive organizations.

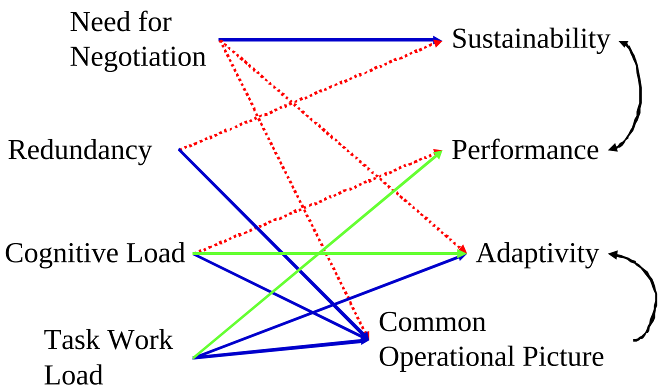

Figure 1: Predicting Performance and Adaptivity

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Instance-Based Decision Making in Dynamic Environments: Modeling the Learning Process

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This paper presents a cognitive model of how people learn to make better decisions in dynamic environments. I argue that, in dynamic environments, the main learning structure is an "instance" representing the knowledge of the situation (decision context), the decision (one among the possible actions), and an evaluation of the decision results (utility). Decision making behavior in dynamic environments turns from rule-based to instance-based as decision makers become familiar and confront similar situations. A cognitive model has been designed to illustrate this form of learning in a dynamic resource management task. Results from the cognitive model support the instance-based ideas and suggest that instances guide the recognition to relevant task cues. Decision makers become more selective in their judgments without a prescribing rule.

Learning in Dynamic Decision Making

Dynamic Decision Making (DDM) is characterized by multiple, interdependent decisions occurring in real-time in a continuously changing environment (Brehmer, 1990). DDM involves making decisions under uncertainty in situations in which not all possible eventualities are available nor it is possible to evaluate them within a time frame.

Classic theories of judgment and choice such as the Expected Utility Theory often ignore the complexity and dynamic characteristics of the real world, and the cognitive limitations of decision makers, assuming that decision makers always choose the option with the maximum utility. Optimal decision making is impossible in DDM. Optimality requires assessing all the alternatives and predicting the likelihood of their success, which is impossible given limited information, high uncertainty and limited time. Evidence suggests that the rationality of human decision making is bounded (Simon, 1957). Bounded rationality results from both, cognitive limitations and environment constraints.

A general question that drives my research is: How do decision makers improve their performance in dynamic environments? The traditional approach to improving decision effectiveness suggests the use of heuristics or general rules of action (Newell & Simon, 1972). Research has shown that a wide variety of decision rules are generally superior to unaided human decision making in some situations. However, the application of decision rules usually proves too restrictive for real world tasks (Einhorn & Hogarth, 1981; Gilboa & Schmeidler, 1995; Klein, 1997). In contrast to rule-based approaches, instance-based learning theories argue that skill development can be explained in terms of the storage of specific solutions to specific problems (Logan, 1988; Gilboa & Schmeidler, 1995). In a recently proposed Instance-Based Theory of Learning in DDM (Gonzalez, Lerch and Lebiere, 2001) we argue that, in dynamic environments, the main learning structure is an "instance" representing the knowledge of the situation (decision context), the decision (one among the possible actions), and evaluation of the decision results (utility) (SDU instance). Learning occurs by a gradual movement from rule-based to instance-based decisions, as decision makers confront and recognize similar situations. A cognitive model has been designed to illustrate this form of learning in a dynamic resource management task. The model is summarized next.

Instance-Based Decision Making in the WPP task

The Water Purification Plant (WPP) is a resource allocation task, isomorph of a real-world mail sorting task. WPP is a dynamic, real-time simulation in which decision makers distribute water to multiple factories by activating and de-activating pumps. Figure 1 shows a snapshot of the simulation. Water is assigned to different tanks based on a scenario unknown to the decision maker (a scenario defines the amount of water and the time of assignment). Due to electricity constraints, decision makers may only activate 5 out of 44 pumps in the system. Each factory has a deadline by which it needs to receive all the water from the system. After each deadline, the gallons of water not distributed on time to each factory are calculated and reported to the decision maker as a form of feedback. The best performance in this task is zero gallons missed.

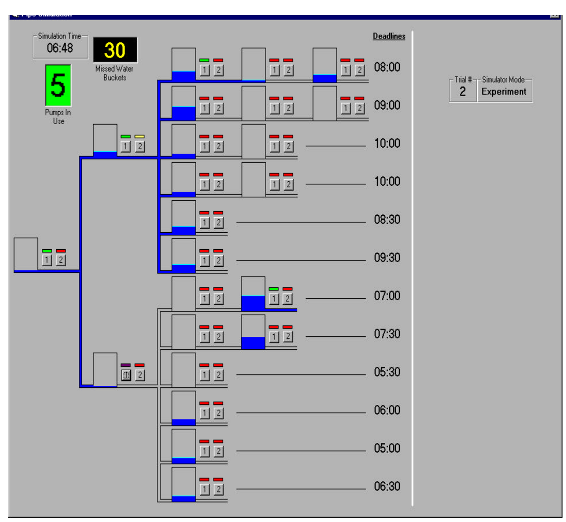

Figure 1. WPP snapshot

WPP does not have one "optimal" solution. There are many sequences and combinations of decisions that may lead to the best performance. A heuristic that has proved to be better than random assignment in this task is the Time rule (Lerch, Gonzalez, Harter, 2001). The Time decision rule prescribes to activate the pump (s) for the tank with the most immediate deadline. This rule is basically the earliest time rule in operations management. The utility of the decision is calculated by subtracting the deadline time of the tank associated with the activated pump minus the time when the decision was made.

The ACT-R cognitive model: CogWPP

ACT-R (Anderson and Lebiere, 1998) is a cognitive modeling architecture that has been used in a wide range of tasks since its introduction in 1993. In ACT-R it is possible to represent knowledge in two forms: procedural (If-Then rules or productions) and declarative (chunks). It is also possible to retrieve this knowledge according to a set of performance/learning methods. A cognitive model of the WPP task (CogWPP) was implemented in ACT-R. The model assumes the user knows the Time rule, prior to the availability of instances. SDU instances are implemented into a chunk structure, where Situations are described by a tank and its characteristics (e.g., amount of water, chain value, deadline, etc.), Decisions are activation and deactivation of pumps and Utility is implemented in time units (minutes left to a deadline). SDU instances are generated for every decision-making situation confronted. When presented with a decision situation, the CogWPP evaluates it using any of two production rules: Instance-Based-Judgment or Rule-Based-Judgment. Figure 2

shows the English-like version of the Instance-Based-Judgment production. Making judgments by instance or by rule is determined by the similarity between the current situation and situations experienced in the past. CogWPP attempts to use stored knowledge by firing the Instance-Based-Judgment production first. If no similar situations have been experienced in the past, then CogWPP chooses to fire the Rule-Based-Judgment production. In the Instance-Based-Judgment production, CogWPP uses a scaled linear difference between two numbers to determine chunk similarity. When at least one instance in the past is found to be similar enough to the current situation, CogWPP performs a *Blending* of the utility value of all similar instances from the past to produce the utility value of the newly experienced situation. Blending allows the retrieval of an aggregate result of a set of memory chunks rather than only one chunk (Lebiere, 1998). The new SDU instance created by this process has an utility value representing the knowledge of similar instances from the past.

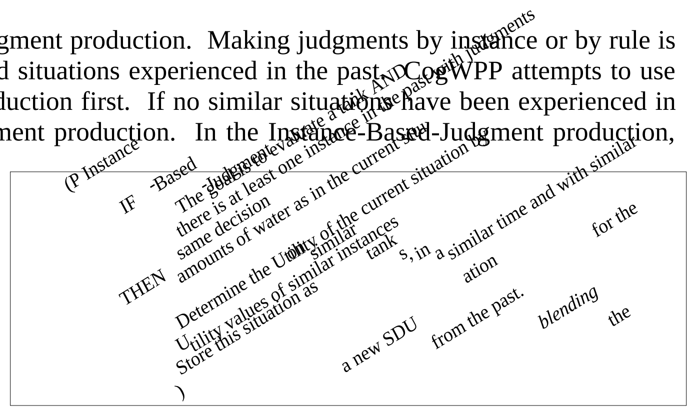

Figure 2. Instance-Based-Judgment production

Results from CogWPP

Data was collected from CogWPP by running the model 18 times and storing basic statistics. In empirical learning experiments we have conducted, subjects ran the simulation a maximum of 18 times during three days at a high speed (Lerch, Gonzalez and Harter, 2001). We used one of the experimental conditions used in past experiments to compare the performance of our model with real users performance. Figure 3 shows the learning curves from empirical and model data averaged per day. As indicated by the data, CogWPP performs better than subjects. I believe due to the way the model is managing resources (pumps). The model keeps pumps busy most of the time, while real subjects become more efficient over time. Refinement of the model based on empirical data comparisons is under development.

The first theoretical prediction is that learning can occur by the accumulation, use and refinement of instances.

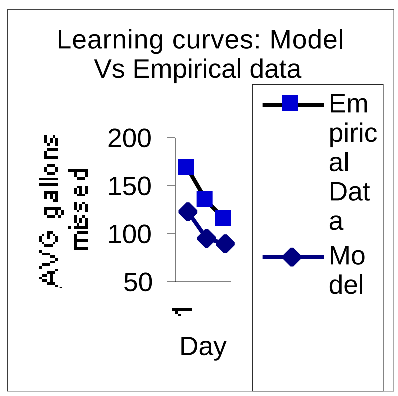

Figure 3. Model Vs Empirical data

We expected a gradual movement from the use of rules to instances. Data from the model indicates that the number of judgments by example exceeds judgments by rule on the second trial. Figure 4 indicates that the rule use drops considerably during the first five trials. Our model allows the use of SDU instances from the very first trial. That is, CogWPP takes advantage of knowledge acquired within and between trials. By the 18th trial, less than 3% of the judgments were done by rule.

Another theoretical prediction is that experts' performance is highly perceptual, based on recognition rather than analytical strategies. Figure 5 shows the utility slot values of the SDU instances per day, categorized by the tank's water amount. The figure indicates that the utility value is larger the larger the number of gallons of water in the tank. Utility value is larger for tanks containing 21 to 30 gallons of water than for tanks containing between 0 and 10 gallons.

Results from the cognitive model indicate that instance-based learning might explain the way decision makers improve performance in dynamic environments. Decision makers may start by using a general heuristic, but as they store examples of situations and refine the impact of their actions they use their knowledge by recognizing the similarity of the situations they confront. Results also suggest that instances guide the recognition to relevant task cues. Figure 5 indicates that the model learns to pay more attention to the amount of water in the tanks over time. It also indicates that tanks that have more water are more important than tanks that have less water. The initial time heuristic provided to the model did not include such knowledge. We believe this demonstrates the development of selectivity during the recognition process. Decision makers recognize typical situations by attending to important task cues *without knowing* how they do the recognition.

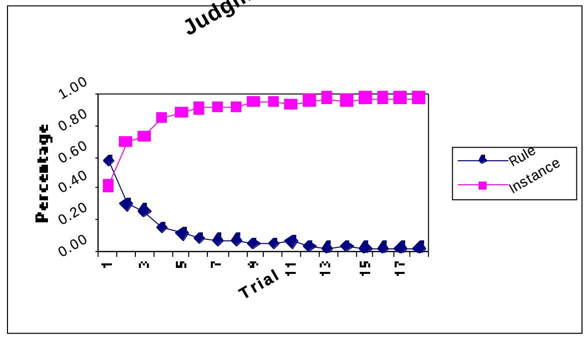

Figure 4. Rule Vs Instance judgments

Conclusion

This paper summarizes an instance-based decision making theory that has been explained extensively elsewhere (Gonzalez, Lerch, Lebiere, 2001). I investigate the process and cognitive structures involved in decision making in dynamic environments. Classic theories of decision making under uncertainty are too simplistic and fail to explain and predict skill development within human cognitive capabilities in dynamic situations. These theories often ignore the complexity and the dynamic characteristics of the real world. Up do this moment, I don't know of a "rule" to solve the WPP task. There is no mathematical representation that would lead to best performance. But I know that, even if such rule exists, it would be too complex for humans to follow in order to learn and improve performance. Therefore, failing to explain how real people actually make decisions in these tasks. This paper presents what I think is a more plausible explanation of the way humans learn to make better decisions in dynamic environments. Cognitive modeling is a technique that helps us explain a theory and predict performance within a cognitive framework, in the reality of human mind. Much work needs to be done to refine and improve our cognitive model in order to use it as a tool to predict learning in DDM. In particular, I am currently studying two variables: time pressure and working memory. I am interested in investigating the cognitive strategies that humans use to deal with time pressure in DDM and their interaction with the humans cognitive abilities.

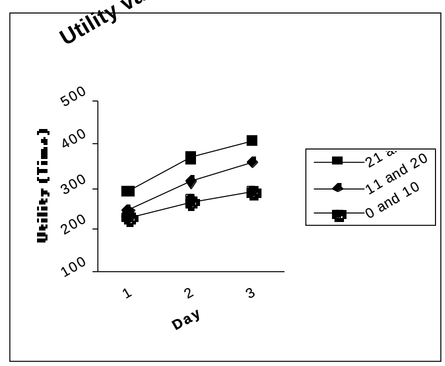

Figure 5. Utility and Water volume

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Learning and Transfer in Dynamic Decision Environments

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Dynamic decision tasks such as firefighting, process control, and bargaining, require repeated decisions under time pressure. A common difficulty for learning in these tasks is that outcomes are frequently the result of sequences of decisions, not just one decision in isolation. For instance, a bargainer who starts with a very high asking price that is rejected may then be able to get a lower price accepted. If the bargainer is skilled, the lower price will still be higher than what would have been accepted as an initial offer. The price improvement is not due to either one of the as ing prices in isolation but to their sequence (Cialdini,1984).Experimental investigations of decision makers in tasks with similar and more complex sequential dependencies indicate that decision makers show performance improvement (e.g., Diehl &Sterman,1995;Gibson,2000),but in the time allotted, they are less able to develop knowledge about the task that they can apply to contexts they have not yet seen. With practice, our example bargainer might get better at manipulating sequences of prices on a specific item within a narrow range, but she will have difficulty applying this s ill to other items or price ranges.

Can theory provide guidance in designing a decision environment to help this bargainer? Poor ability in transferring knowledge between different task contexts is so pervasive in repeated decision making that many theories suffice with the assumption that that decision makers learn based on success and failure in specific contexts (e.g., Dienes & Fahey, 1995; Fudenberg & Levine, 1998;Roth & Erev, 1995),effectively ruling out the possibility of transfer (Logan, 1988).However, evidence from functioning dynamic environments suggests that expert decision makers routinely and successfully apply their knowledge to novel contexts (Kanfer &Ackerman, 1989; Klein, Orasanu, Calderwood, & Zsambok, 1993; Joslyn & Hunt, 1998). Experienced air traffic controllers, refighters, and police dispatchers are all able to perform more effectively in novel situations than less experienced decision makers.

This contrast in theory and results suggests that the initial question can be further refined:(1)Under what conditions does theory predict that experienced decision makers are able to transfer their knowledge to new contexts?(2)What different types of information does theory predict will help novice decision makers? To help address these questions, this paper develops a two-stage model of learning in dynamic tasks. In stage one, decision makers form internal representations of the task situation from available environmental stimuli. Then, in stage two, they use these internal representations to decide on an action. As decision makers 'internal representations evolve with experience to better recognize task situations requiring similar decisions, the two-stage model predicts that decision makers will become better at transfer.

The next section reviews prior work in dynamic decision making to help con- strain construction of the model. After that, the model is elaborated with comparison to a one-stage model that learns based on success or failure in specific contexts, with no internal re-representation of contexts, as is frequently assumed in studies of repeated decision making. Then both models are instantiated in a simulation experiment to make predictions for human learning and transfer in an Internet-based bargaining task. Both models correctly predict the effective- ness of knowledge supplied to help naïve decision makers. The two-stage model provides significantly closer fits and correctly predicts the direction of the learning trend for decision makers in a new bargaining task where features from the original tas are still relevant but with different decision implications.

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Modeling the Effect of Uncertainty on Attention Seeking and Decision-Making

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Abstract

We consider a formal model of group decision-making in which each participant presents an expected value to the decision-maker for the attention and resources the proposer requests. The decision-maker maximizes the expected value of the set of actions taken, subject to constraints, the most important of which is the decision-maker's time. Proposers, intelligent semi-autonomous agents, create a "value tags" indicating the expected net benefit to the decision-maker, and the decision-maker encourages the creation of value tags which he/she can easily and quickly evaluate. Decision-makers inflate or deflate proposers' value estimates based on experience and on similarity to / difference from previous successful proposals, and agents modify their presentations based on success and failure of proposals.

Formally, this means that agent j presents a value B_{ij} for having him take action i, and requires T_{ij} of the decision-maker's time to evaluate the proposal and C_{ij} of the resources under the decision-maker's control to carry out the action if adopted; the decision-maker modifies B_{ij} to B'_{ij} and C_{ij} to C'_{ij} and atttempts to solve

max __ A_{ij} (B'_{ij} - C'_{ij}), where A_{ij} is 1 if proposal ij is adopted, 0 otherwise,

subject to __T_{ij} _ t and __C'_{ij} _ c , that is, constraints on the decision-makers total resources available and (more important) the time the decision-maker is willing to devote to considering proposals and making these decisions.

Note that the set of proposals available for consideration may involve more total consideration time __T_{ij} than is available. Knowing this, the decision-maker can solve the above problem using estimated B' and C' coefficients and eliminate from the agenda the proposals unlikely to be adopted. If a given agent has no proposals likely to be adopted, that agent may be eliminated entirely from the decision process.

In this continuation of previous work with this model, we focus on the effect of uncertainty. Uncertainty is known to cause changes disproportionate to the true risk to the organization and the decision-maker, especially in large, complex decision processes and organizations. The effect of uncertainty on the time required to make a decision explains the apparent disparity: the introduction of a small number of alternatives and a small amount of chance variation can increase the attention required to make an optimal decision much more than it increases the potential loss associated with a reasonable but sub-optimal choice.

In terms of the formal model, this means that uncertainty not only changes the B'_{ij} and C'_{ij} terms, it also increases T_{ij} -- sometimes by a large amount, depending on the decision-maker's sophistication in dealing with uncertainty. One strategy for an agent with some proposals likely to succeed, therefore, is to expand the consideration times required by his and other proposals to drive competitors off the agenda.

We consider applications of this idea to a number of areas of activity. In information warfare, this principle explains the value of transmitting many bogus messages rather than limiting transmission: the interceptor's information and decision-making burden increases exponentially in the number of messages he must evaluate and choose among. (For example, conducting all the pairwise comparisons among n alternatives requires 2^n decisions.) Similarly, a corporation attempting to disguise its marketing plans is better off leaking misleading cues to its intentions than trying to conceal everything.

In international relations, creating uncertainty about one's intentions can be highly effective, forcing the adversary to prepare for multiple threats and increase resources and efforts devoted to threat detection and evaluationWe discuss how this analysis explains well-known, poorly explained phenomena ranging from information warfare and security to international relations to dating, concentrating especially on the deliberate introduction of uncertainty as a competitive weapon. An especially interesting example of this is the Reagan administration's Strategic Defense Initiative, which strained the Soviet military and intelligence system to the breaking point at modest expense to the U.S.: precisely because no one could tell whether the actual system would ever work, the Soviets could neither justify a preemptive strike nor ignore the system's potential. Their decision-making system collapsed under the strain.

In dating, we finally have a more or less scientific explanation of why the nice guy rarely gets the girl: if he is too predictable, he doesn't get enough attention to stimulate her interest! He is best advised to vary his behavior more, find and appeal to her major interests -- or arrange to get stuck with her in an elevator.

An Evolutionary Model of the Double-loop Learning as a Module of Organizational Learning

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Extended abstract

We develops a basic framework for evolutionary approach to organizational learning in agent-based modeling., the framework which could provide models to describe the essentials of mechanisms driving the organizational learning and the actual methods for simulation experiments to get insights of the organizational learning.

Based on an evolutionary approach, this paper particularly develops a basic model of the double-loop learning that is an essential part of organizational learning. The central problem on the double-loop learning is concerned with how the internal models of the members in an organization can be improved and shared. The model provided here is formulated based on a basic distribution model often used in economics. The model can express the levels of organizational learning. We concentrates on the exploration of the essential principle of the double-loop learning, and puts some rigorous assumptions on the other levels of the organizational learning such as single-loop learning or the detail structure of organization. Using this model, we perform some simulation experiments by genetic algorithms to get essential insights on the way how and what information should be utilized for effective double-loop learning. We can call such use of simulation "inverse simulation."

First we describe the characteristics of agent-based modeling as an essential way to reveal the nature of complex systems especially including social systems. Agent-based modeling is basically a modeling method to deal with the multi-agent system in which each agent behaves based on his "internal model" of the situation.

Evolutionary approach to organizational learning in agent-based modeling shows a way that each agent involved in a complex situation learn the situation and relevant features in an evolutionary manner. The framework developed in this paper consists of four basic steps. (1) Each agent makes a decision and action independently. (2)Each agent exchanges the results as responses from the situation with other agents. (3) Each agent improves his "internal model" of the situation in some evolutionary manner. (4) Each agent makes a new decision and action based on the improved internal model.

Then we distinguish the core modules of organizational learning processes. (1) Individual single-loop learning: In this process each agent makes his decision based on his own internal model. (2) Individual double-loop learning: Each agent modifies and improves his internal model that can interpret the responses received from the situation after his action. (3) Organizational single-loop learning: An organization makes decisions and takes actions as collective sets of individual decisions and actions. (4) Organizational double-loop learning: In this process the individual internal models are shared as some integrated model with each member of the organization.

We present a specific model to describe the above evolutionary learning process as a learning process of the individual perception of each agent involved in the situation. First we specify a social system consisting of two components, P1 and P2. Each represents a network of agents.

$$P1{:}f_1=a_1u_1+b_1u_2$$
$$P2{:}f_2=a_2u_{12}+b_2u_2$$

where ui is the variable for agent Pi's decision making, uij is the variable for agent Pi's decision making that is predicted by agent Pj. ai,bi take real values. The total system output is

$$z=au_1+bu_2$$

We can see two levels of decision making in the above model. One is the level in which each agent decides the decision making variable ui optimizing his payoff function, and predicts other agents' variables uij. The other level is concerned with the decision of the coefficients a and b as the environmental structure and the distributive rule ai,bi. These decisions are involved in the double-loop learning. The model with the two levels of learning can be formulated as follows.

$$P1{:}f_1=a_1u_1+b_1u_2$$
$$P21{:}f_{21}=a_{21}u_{121}+b_{21}u_{21}$$
$$P12{:}f_{12}=a_{12}u_{12}+b_{12}u_{212}$$
$$P2{:}f_2=a_2u_{12}+b_2u_2$$

The model expresses each agent's internal model and can distinguish the above four modules of the organizational learning process as the relationships of the coefficients expressed in the model. We should notice that this model especially focuses on the double-loop learning process and tries to get insights of the mechanisms of it from simulation results by applying genetic algorithms. Hence although the four modules of the organizational learning process are included all in this model, the other modules except the double-loop learning processes are simplified by putting some assumptions based on rational decision making theory.

Then we develop a simulation model to analyze the double-loop learning in organizational learning by applying genetic algorithm to the learning process of the parameters describing the decisionmaking environment of each agent in the basic model. This paper actually performs some simulationexperiments based on the model and gets some results on the role of information in learning mutualperceptions of agents in the double-loop learning in organization.

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Simulating the Role of Transactive Memory in Group Training and Performance[7]

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Abstract

Transactive memory systems refers to the idea that people in continuing close relationship develop a shared system for encoding, storing and retrieving information from different substantive domains. Previous studies provide both direct and indirect evidence of the positive impact of transactive memory systems on group performance, such as efficient storage and recall of knowledge, trust development in groups, and the benefits of training people together. This paper is an attempt to unify the experimental research on transactive memory and to extend it to a more dynamic setting for larger groups. In this paper, we develop an empirically grounded simulation model – ORGMEM, a multi-agent information processing system, which can be used to explore the formation of transactive memory and how transactive memory affects group performance.

ORGMEM is a multi-agent simulation system that imitates the interpersonal communication, information processing, and decision-making processes in organizations. In ORGMEM, agents are intelligent, adaptive, and heterogeneous. In other words, each agent has access to some knowledge (intelligence), is able to conduct a specific number of tasks, and can learn from each other (adaptation). As socially connected agents, each of them also has a transactive memory about who talks to whom, who knows what, and who does what in the group. During the operation process, each agent is able to conduct a variety of activities, such as communicating knowledge, searching for resources, and making decisions. Over time, organizations receive a series of tasks. Agents work on subtasks assigned by the program, make decisions by combining personal knowledge and information from their subordinates, communicate both technical knowledge and social knowledge, and learn from each other. As a result, group communication structure regarding who talks to whom, skill structure regarding who knows what, and transitive memory change over time.

Through a series of virtual experiments, we find that transactive memory improves group performance, decreases group response time, and increases decision quality. Moreover, the impact of transactive memory tends to decrease or even disappear as group size increases.

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Hierarchies and Transactive Memory Systems: Crafting a Model of Flexible Exception Handling

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Information processing theory describes organizations as information processing systems whose performance is contingent upon the relative fit between the information process capacity of the organization and the information processing demands created by the task environment (Galbraith, 1974). A key element of this theoretical framework is the relationship between organizational structure and the information processing capacity of the organization. In routine, stable task environments characterized by relatively low task uncertainty, the hierarchy is employed to handle exceptions (or situations for which no organizational rules exist). In such cases, the information processing capacity of the hierarchy is sufficient for handling the moderate information processing demands associated with the relatively few exceptions that do arise. However in more complex, dynamic task environments characterized by higher task uncertainty, the number and type of exceptions that occur can quickly overload the information processing capacity of the hierarchy, resulting in degradation of project and project team performance.

This paper describes our logic and methodology for arriving at a set of precise micro-level behavioral mechanisms for representing the type of flexible, expertise-based exception handling processes we associate with more complex, dynamic technical task environments. We take the hierarchical exception-handling framework represented in the current Virtual Design Team (VDT) micro-contingency model as our primary point of departure. We develop our theoretical extensions to VDT by combining elements of VDT's hierarchical framework with elements drawn from transactive memory theory. We operationalize these elements as micro-level behaviors, which we instantiate in an agent-based computational prototype. We simulate the prototype to observe the exception-handling structure that emerges under the assumption of expertise-based (versus solely authority-based) exception handling resolution processes. In this paper, we describe our use of the computational prototype as a formal method for developing our reasoning about these new micro-level behavioral mechanisms, and for generating a set of testable hypotheses related to these theorized micro-level behaviors.

Exception Handling in the Current VDT Model

The assumption of a routine task environment in VDT has made it feasible to represent the exception handling mechanism of the organization as a fixed, vertical reporting hierarchy (Jin and Levitt, 1996). In the current model, actors occupying higher-level positions in the exception-handling hierarchy (i.e. sub-team leaders or project managers) are responsible for decisions about how to handle exceptions. An actor that receives an exception from a subordinate makes a decision about the relative amount of rework that should be completed to repair the exception. This rework decision defines the amount of additional work volume, if any, which is added to the activity's original work volume.

Four characteristics define the current VDT exception handling mechanism. First, actors refer exceptions to other actors in the exception handling hierarchy or not at all. Second, a given actor refers all of its exceptions to a pre-specified actor, i.e., choice of receiving actor does not vary as a function of the sending actor's task or its attributes. Third, actors don't consider the technical knowledge of the receiving actor as a criterion for exception referral. Fourth, decisions specifying the amount of rework that should be completed to repair errors (or implement design changes) constitute the only means by which exceptions are handled. A key assumption underlying the current VDT exception-handling framework is that all exception-handling expertise resides in the formal reporting hierarchy, and that expertise increases with level in the hierarchy.

Extending VDT to Modeling Non-Routine Technical Work

Evidence from prior testing of the VDT model suggests that the assumption of a fixed, vertical exception-handling structure holds relatively well for organizations engaged in relatively routine technical work. For instance, in modeling routine development of a commercial satellite launch vehicle, [8] the current VDT model accurately predicted the schedule backlog in an external sub-team responsible for supplying a critical subsystem (Kunz, 1998). In routine technical projects, much of the work effort involves relatively well-understood production activities (e.g., routine subsystem design) involving relatively low levels of task uncertainty. When customers request certain design changes, or when internal errors occur, supervisors or managers issue rework decisions that specify the amount of additional work that should be completed to repair errors or incorporate design changes. However, for organizations involved in less routine technical projects, such as in new

[8] The VDT model was used to predict project risks associated with accelerated development of the launch vehicle. We describe the project as "routine" since existing methods and technologies were used during development of the satellite launch vehicle.

product development involving new technologies, or in post-merger technology integration projects, rework is not always applicable to the type of exceptions that can arise. Instead, exceptions may require access to specific technical and process knowledge that resides outside of the project reporting hierarchy. In many cases, the required expertise is external to the focal organization, if not the firm itself. For example, in a study of information exchange in R&D organizations, Allen (1997) found that engineers spent as much time consulting with experts who were external to their organization as they did consulting with internal experts. Thus, an upward flow of exceptions and downward flow of repair decisions (as represented in the current VDT model) does not capture the more complex, lateral information flows we associate with exception handling processes in non-routine technical projects.

In addition, workers in these project settings do not always turn to the same individuals for information and advice in all exception-handling situations. Empirical research suggests that individuals rely on an understanding of “who knows what” as means for locating specific others for assistance in handling exceptions that arise with specific activities. For example, McDonald and Ackerman (1998) found that software programmers used program change history records to identify potential experts for handling exceptions that would arise in software technical support. This evidence suggests that a worker’s choice of who to turn to is not decoupled from the attributes of the task generating the exception, but is integral to it. Thus, for non-routine technical task environments, a more representative model of exception handling is one that:

1. is flexible, allowing for lateral as well as vertical exception referral,
2. includes consultative (vs. solely decision-based) exception resolution processes,
3. takes into account the knowledge of others (i.e., who knows what), and
4. takes into account the knowledge requirements of the activity linked to the exception.

Transactive Memory and Exception Handling

We speculate that workers in non-routine technical projects rely on their perceptions of “who knows what” as a key mechanism for identifying and selecting candidates for exception referral. We conceptualize this micro-level process in terms of a ‘transactive memory system,’ which describes a specialized division of cognitive labor wherein members of a group assume responsibility for learning information within their own knowledge domain, while expecting others to do the same (Wegner, 1987; 1995). A key implication of this theory is that members who share a transactive memory system benefit from access to a larger pool of information across multiple knowledge domains, without incurring the costs (i.e., time and effort) associated with learning the same information held by all other members in the system (Hollingshead, 1999). This work takes elements from transactive memory, and applies it to the issue of exception handling in non-routine technical projects.

Two key factors motivated our interest in applying transactive memory to exception handling in non-routine technical projects. First, we believe individual actions based on perceptions of “who knows what” represents an axiomatic (and testable) micro-level mechanism associated with technical exception resolution processes. Second, we believe a behavioral mechanism that links transactive memory mechanisms to the specific knowledge requirements of tasks would extend the current VDT model in a direction that would allow us to conduct virtual experiments exploring the impact of actual and perceived distributions of expertise on exception handling outcomes. Our thesis is that combining elements of transactive memory and hierarchical VDT exception-handling mechanisms will move us closer to a more representative model of flexible exception-handling processes employed in non-routine technical work.

	Actor1	Actor 2	Actor 3
HasKnowledge	B	B	A
ReportsTo	Actor 3	Actor 3	Actor 3
IsResponsibleFor	Activity 1	Activity 2	Activity 3
	Activity 1	Activity 2	Activity 3
RequiresSkill	A	B	B

Table 1. Actor and activity attributes and attribute values used in the computational prototype.

Description of the Prototype and a Case Example

To arrive at a more precise theoretical model of flexible exception handling, we employed a simple computational prototype for theory development (Carley, 1999). Our goal was to instantiate a small set of transactive memory mechanisms in an agent-based computational prototype,[9] then simulate the prototype to observe the *operational exception handling* structure (i.e., the employed network) that would emerge from micro-level interactions between actors assuming expertise-based (versus solely authority-based) exception handling behavioral mechanisms.

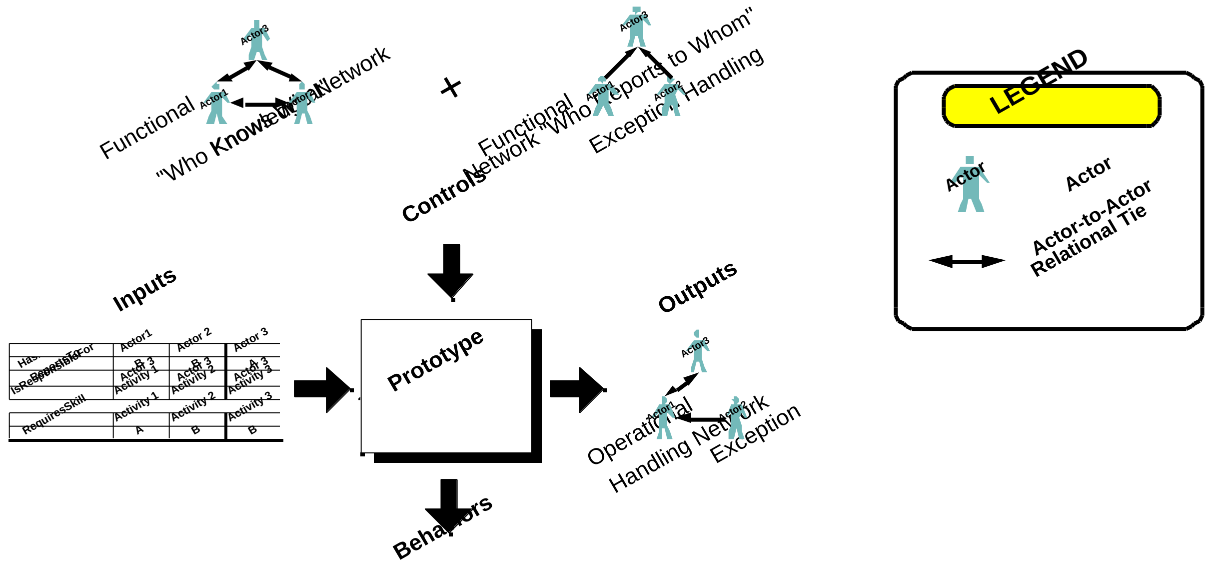

Figure 1. Representation of inputs (left) and outputs (right) used in the computational prototype. Controls (top) refer to network constraints used in the model. Behaviors (bottom) refer to the actor action cycle actors in the model follow, assuming expertise-based exception handling.

To ground our analysis, we employed a synthetic case example, which explicitly described the specific organization (i.e. actors, actor-to-actor relationships) and task environment (activities, activity-to-activity and actor-to-activity relationships) that we modeled in the prototype. Core inputs to the model are given in Table 1. We drew upon the construct of 'organizational proximity' described by Axelrod and Cohen (2000) to infer the *functional knowledge network* (i.e., network defining perceptions of "who knows what" across the group) that would apply to the organization represented in the case example. Applying this construct, we assumed members with direct or indirect reporting relationships to be organizationally proximate, and thus to be aware of each other's work-related expertise. We operationalized the functional knowledge network as a 3 x 3 relational matrix that defined perceptions of "who knows what" for the organization. Thus, for the case example, we assumed the functional knowledge network to be fully connected.

Observations and Inferences

Figure 1 shows the inputs and outputs of the prototype. The output consisted of relational data, identifying which of the three actors each actor turned to for exception-handling information, assuming expertise-based search. We captured this data in a 3 x 3 relational matrix, and display it in Figure 1 as the operational exception-handling network. By inspection, we observed a difference in the structures of the emergent and functional exception-handling networks. We explain the differences between these two networks as consequence of expertise-driven (versus solely authority-based) information search. With expertise-driven search as our reasoning framework, we observed two distinct exception-handling situations encountered by actors in the case example. We refer to these as *Type I* and *Type II* exception handling situations. In Type I situations, an actor has an exception that requires information *internal* to his areas of expertise. In Type II situations, an actor has an exception that requires information *external* to his areas of expertise. These two new exception-handling situations, which we elaborate, represent a key departure from the current VDT exception handling process in three ways: (1) actors now consider the *nature* of the exception generated (as internal or external to the actor's areas of expertise), (2) actors now employ categorization of exceptions (as Type I or Type II) to establish the criterion used to search for appropriate candidates for exception referral, and (3) actors now consider the expertise of other actors as a *contingent* factor for exception referral.

[9] We used the PowerModel object-oriented development platform, produced by IntelliCorp , Inc. for development of the computational prototype.

Thus, Type I and Type II exception-handling situations constitute circumstances in which actors apply social (i.e., transactive memory) and decision-making (i.e., choice selection) intelligence in the exception handling process.

We conducted a second analysis, this time with the purpose of interpreting Type I and Type II exception-handling situations through the lens of transactive memory theory. Transactive memory research by Hollingshead (1999) examined relative similarity of expertise between interacting agents as a key dependent variable affecting individual learning outcomes. Findings from this research suggests that *relative similarity* of expertise (between individuals in a transactive memory system) can be used to predict whether a given individual is more or less likely to learn information internal or external to his existing areas of expertise. Our interest was to apply the hypotheses derived from Hollingshead's (1999) findings to infer a set of predictions regarding likely *outcomes* of actor interactions assuming Type I and Type II exception handling situations. This led to the following hypotheses, which states our micro-level behavioral theory.

Proposition 1a. Actors with Type I exceptions are more likely to employ an *ordinal* assessment of expertise (i.e., relative level of expertise) in locating other actors for exception referral, and will preferentially select actors with higher relative expertise (compared to their own).

Proposition 1b. Actors will learn more within their own domains of expertise as a result of interacting with other actors with similar (but higher) expertise.

Proposition 2a. Actors with Type II exceptions are more likely to employ a *binary* assessment of expertise (i.e., presence or absence of expertise) in locating other actors with dissimilar expertise (relative to their own) for exception referral.

Proposition 2b. Actors will not learn (substantively) more information within their own domains of expertise, nor will they learn (substantive) information in the new domain as a result of interacting with other actors with dissimilar expertise.

We elaborate our reasoning underlying these hypotheses and describe a preliminary test plan for validating these theorized micro-level behaviors.

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A Model for Creative Ontogenesis

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One of the most important questions in the social sciences is the exact definition of cognitive ontogenesis in dependency of social environment, i.e. the cognitive development of a learning system which gets informations from its environment and organizes its own evolution by constructing cognitive representations. Berger and Luckmann (1966) have shown that the "construction of reality" consists in the socially regulated construction of world views and the actions on the basis of these perceptions of reality. Each exact theory of society depends on the possibility to model these processes in an exact manner.

The formal system which is demonstrated here models different cognitive operations which together are an important part of cognitive ontogenesis:

1. Each cognitive development is based on learning, that is in particular the association of informations with specific concepts. The term "concept" is used here in a general sense. Conceptual learning takes place if the learner is able to associate different sensual informations with a certain symbol like "dog" or "machine"; conceptual learning can also be the association of specific effects with a particular cause - the wetness of the street is caused by rain and in turn the association of ones own actions as the cause of effects in the environment; conceptual learning enables the learner also to identify certain actions with moral valuations - the theft of money is a crime, the hitting of other people is a cruelty. In the early phases of cognitive development these learning processes are usually "supervised", i.e., the learner is trained in the task of associating certain informations with particular concepts by immediate responses of its environment - parents, teachers and so on., but also of the physical environment as in the case of the effects of certain actions.
2. Concepts are mainly learned as separate units. Another task for a learning system is to order and connect the different concepts. This is done by the construction of semantical networks which systematize the concepts learned during the processes of a). This cognitive operation is usually performed in an unsupervised manner, that is without immediate response by the environment. Therefore these construction processes are a first kind of creative operations. Classical examples for such networks are the formations of biological categorizations or the construction of moral systems including, e.g., religious explanations and legitimizing of moral concepts.
3. A cognitive system has to associate informations with concepts also if it gets new informations but no concepts. Then it has to construct concepts by its own which in the long run of course are valuated by the environment again. This creative construction is performed mainly by formations on analogy: the system uses a certain logic which it has learned in a supervised manner and applies to the new informations. For example, if a student of mathematics has learned the technique of proof by contradiction when learning the famous proof about the infinity of prime numbers then he/she is able to see a logical analogy to this problem in another problem and to use this particular method. In a more simple manner a child forms analogies when it sees an unknown animal and uses a logic of classification which it has learned earlier: a creature is named "fish" if it swims in the water and looks like a fish. A philosopher, to give a third example, has learned that each effect has a cause. Therefore he concludes by using analogies again that the universe also must have a "first cause" which gives him the well known ontological proof of the necessary existence of god.
4. Concepts associated directly with environmentally given informations may be called "first order concepts". A creative cognitive system is also able to construct "second order concepts" which are associated with sets of first order concepts and not with environmental informations. The concept "mammal" is associated with first order concepts like "dog", "cattle" and so on. The enlargement of the concept of "number" in the history of mathematics is a more sophisticated example: natural numbers are obtained by observing the characteristics of sets of things, i.e., their size. The more advanced numbers like real numbers are defined exclusively by referring to number concepts already defined. A cognitive system can construct this way hierarchies of concepts which are the foundations of any complex world view.

If one wants to analyze the impact of a social environment on cognitive ontogenesis then the model described here allows to investigate these impacts on all levels a) – d). For example, an environment may give a lot of different informations to the learning system or it may not. The cognitive system will of course be influenced by the degree of "heterogeneity" the environment offers.

The formal system which models the operations a) – d) consists of different neural nets which are connected in specific ways. In principle it is of course possible to model learning and creative processes with other formal systems also. For example, Holland has shown that certain cognitive and learning processes can be modeled with so called "classifier systems", i.e., rule based systems which are varied by genetic algorithms (Holland et al. 1986). In my opinion artificial neural nets offer more possibilities because there are already a lot of different types of neural nets available whose combinations allow the modeling of rather different cognitive processes.

The difference between the operations a) – d) is modeled by distinguishing between first order and second order networks. First order networks operate with supervised learning and the construction of analogies on the one hand and the construction of semantical networks on the other. The main idea is that all first order networks are connected in the sense that they are able to exchange data, that is environmental informations and the results of their respective operations. It is also possible that the networks correct each other. Second order networks are of course also connected with the first order ones which give the "raw material" needed by the second order networks. More details will be given during my lecture.

Apparently such a formal system allows to investigate different processes of cognitive ontogenesis and a) the effects of different environments on identical cognitive systems and of b) the consequences of differences of cognitive systems which exist in an identical environment. In particular it is possible to model rather different distinctions between singular cognitive systems: they may differ in their ability to learn the associations of informations and concepts, they may be different in constructing semantical networks or the formations on analogy and different also in generating second order concepts. The effects of such differences on a cognitive ontogenesis can be studied in detail. By varying certain features of the environment too (see above) rather complex learning biographies can be investigated.

The model described so far has still an important deficit. It operates under the assumption that its own code is the same as the code which the environment uses when giving informations and feed backs. In reality this is of course often not the case. Imagine a young man who tells a young woman "I love you" and sees the woman turning away from him and speaking to another man. The answer of course is clear but obviously given in quite another code than the young man used. Therefore the model must be enlarged with an "valuating" net which translates the environmental informations into the code which is used by the cognitive nets. Some considerations about such valuating nets will be given at the end of the lecture.

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Organizational Differentiation: The Population of Web Search Engines

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Search engines help millions of people to navigate through the gargantuan amount of information on the web, and have therefore acquired a key role in modern society. Besides being providers of an important service, search engines are also business companies, and can therefore be studied from a social science perspective. It is surely interesting to examine whether the internet as target area of operation makes the dynamics of a dot-com population different from more traditional sectors of the economy.

The web search engine market seems destined to be dominated by large players, because of extreme economies of scale. What we see is quite the opposite, though. The number of large players, English language general search engines, has stabilized at around 15-20 for 5 years, whereas since the beginning of 1997, there has been a rapid growth of the number of small search engines in virtually every corner of the web, from Japan to Croatia. We estimate that currently 90% of the players are small, and this number still increases.

How can we explain this small firm proliferation? To answer this question, we first take a look at some recent developments in organizational sociology that try to deal with similar empirical observations.

The observation of a proliferation of small newspapers in the United States triggered the development of resource partitioning theory (Carroll 1985), a part of organizational ecology. According to this theory, generalist organizations compete for the center of their market. If smaller generalists are outcompeted by large generalists with scale economies, empty "niche pockets" open up for small specialist organizations to thrive. Resource partitioning theory, however, assumes markets to be mature. In ecological parlance, markets are supposed to have reached their "carrying capacity". For the market of search engines, in which the consumer base is still growing rapidly, this assumption does not hold.

A variation of resource partitioning theory, the so-called "sphere packing" model (Péli and Nooteboom 1999), does not have this drawback, as it applies to all stages of a market. In this model, proliferation of small organizations is explained by the increase of the dimensionality of the resource space. As the number of consumer taste dimensions increases, the empty space between the incumbent organizations _ represented as multidimensional spheres _ increases, allowing for an increasing number of smaller spheres to fit in between. The sphere packing model hinges on the assumption of a homogeneous distribution of consumers over all dimensions of taste. Moreover, spheres are not allowed to intersect.

With respect to the market of web search engines, both assumptions seem to be overly strong. First, a homogeneous distribution of consumers over dimensions of taste in fact implies a very heterogeneous market, in which no taste is more common than any other taste. Second, many consumers of search engines actually make use of more than one search engine. In fact, consumer base intersection is important to understand the competitive dynamics of this population of organizations.

Still, the idea that an increasing dimensionality of a resource space can account for the proliferation of small players remains appealing. A well known feature of multidimensional spaces is the so-called "curse of dimensionality" (Bellman 1961). As the number of dimensions of a hypersphere increases, the volume of the outer part of the sphere (the integral taken from $(r - \varepsilon)$ to r, with r the radius of the sphere and $(0 < \varepsilon < r)$) increases more rapidly than the volume of the inner part. This result does not only hold for spaces in which the resources are distributed homogeneously over the dimensions. It can be generalized to spaces in which the resources are, for example, distributed normally.

This fact allows us to formulate the following very simple model: we assume resources for search engines to be normally distributed. As time goes by, consumers become more articulate in why and how they choose between different search services available on the market. As a consequence, the number of dimensions on which search services are evaluated increases. The curse of dimensionality ensures that, as dimensionality increases, an increasing proportion of the resources is to be found in the periphery of the market, i.e., the tails of the multidimensional Gaussian. Here, consumers with special tastes are targeted by specialist organizations. Assuming that there is a limit on the range of tastes a company can appeal to, the periphery of the market will harbor a relatively large number of small companies, while the markets center contains a relatively small number of large companies. Last but not least, in our conceptualization, there is niche intersection.

To explain the proliferation of small search engines, we have to show that the dimensionality of the search engine market has increased since its inception. In order to do that, we have collected quarterly data on 137 search engines from the end of 1994 (when the search engines first appeared on the web) until the last quarter of the year 2000. For this population of organizations, we measured the size of their consumer base, the pairwise overlap of the consumer bases for every pair of organizations, as well as other organizational variables, such as language and origin. From our data, we can clearly see that the number of dimensions on which search engines are evaluated, has increased. To complement our observation, we constructed a measure of pairwise "distance" between organizations. From this measure, we want to estimate the number of resource dimensions. We currently work on an algorithm to accomplish this task.

Whether we succeed or not, our data are sufficient to show that indeed the number of dimensions of the market of web search engines has increased. The subsequent increase of resources in the periphery of the multidimensional resource space, due to the "curse of dimensionality", could explain the proliferation of small search engines.

A Computational Model of Computer Virus Propagation

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Extended Abstract

Computer virus infection is the most common computer security problem. This problem has imposed significant amount of financial losses to organizations (CSI, 2000). Even though most organizations have installed anti-virus software in their computers, majority of them still experienced computer virus infection (ICSA, 2000). Most anti-virus software could not detect a new virus unless it is patched with the new virus definition file. Disseminating the new virus information and patches is hence important to raise user awareness. However, little research has focused on evaluating the effectiveness of disseminating new virus information on reducing virus infection. We hence propose a corporate response model to investigate the effectiveness of warning message propagation. In addition, we use the model to study the influence of social network topology on the virus and warning message propagation.

A computer virus is a segment of program code that will copy its code into one or more larger "host" programs when it is activated. A worm is a program that can run independently and travel from machine to machine across network connections (Spafford, 1990). We will refer computer viruses to both computers viruses and worms in Spafford's definition since most viruses today can be propagated in both ways.

Epidemic propagation models (Bailey, 1975) have been applied on modeling the propagation of computer viruses (Kephart and White, 1993). Simulation models have been used to discuss the influence of the network topology (Kephart, 1994)(Wang, 2000)(Pastor-Satorras, 2001). However, neither the empirical topology data has been collected nor the characteristics of the topology have been further studied. In addition, the warning message propagation is related to the network topology, which could be a different network from the virus propagation network.

A corporate response model is developed to describe computer viruses propagation and the warning messages propagation. The components of the model include the inter-organizational social network topology, the computer network topology, the virus propagation mechanism, and the node state transition diagram. The four components are described as follows:

1) The inter-organizational social network topology and computer network topology are both represented as a graph $G = (V, E, W(i,j))$ where V is a set of nodes and E is a set of edges. $W(i,j)$ denotes the link between node i and j where $i, j \in V$. $W(i,j) = 1$ if a link exists between node i and node j and $W(i,j) = 0$ otherwise. We then apply social network analysis (Wasserman, 1994) measures, such as density and centralization, to characterize the network topology in our virtual experiments. A new measure, isolation, is needed to describe the computer virus propagation topology since the isolation nodes are critical to in the propagation process. Isolation of graph G, $I(G) = \frac{|S|}{|V|}$, is defined as the number of isolated nodes divided by the total number of nodes in the graph. Isolated nodes refer to the nodes that do no have any links with other nodes in the same graph. $S = \{ i : \forall j \in V, \sum_{j=1}^{N} W(i,j) = 0 \}$, denotes a set of isolated nodes.
2) The virus propagation mechanisms are categorized as one-to-one, one-to-many, many-to-one, and many-to-many. The category refers to the number of infection source and the number of infection targets at once.
3) The node state transition diagram is used to describe the dynamics of a node over time, such as if a node is infected by a virus or warned by a warning message. The change of states is determined by the propagation of viruses through the social network and the propagation of warning messages through the computer network. We assume that the nodes will receive an automatic warning message if their computers physically connect to a computer that has already had one.

Virtual experiments are conducted by varying the type of topology, the number of nodes, density and isolation. Experiment results show that random graph topology generated by the same density and isolation as real world data set could be used on modeling the social network of computer virus propagation.

In addition, isolation is not an effective strategy for an organization if warning messages are propagated in the network. Isolating an organization from other nodes in the social network could isolate the node from virus infection but isolate the node from the warning messages as well. This result contradicts with many organizations have assumed.

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Evolving Drug Networks

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Various theories of deviance have been posited and tested to understand the use of both licit and illicit drugs. These theories focus on the roles of the peer and family in both the promotion and prevention of drug use. A host of prior research has demonstrated a positive relationship between peers and drug use. (Akers et al, 1979; Brooks et al., 1978; Dull, 1983; Elliot et al., 1985; Glynn, 1981; Hawkins and Fraser, 1985; Hansell and Wiatrowski, 1982; Huba and Bentler, 1980; Jessor and Jessor, 1977; Johnson, 1973; Kandel, 1984, 1985; Kandel and Andrews, 1987; Kandel and Davies, 1991; Kaplan, 1985; Krohn et al., 1988; Krohn and Thornberry 1991; Wister and Avison, 198; Zablocki, 1989) Beyond the common position that local social effects have a strong effect on drug use, they differ significantly and generally fall under two traditional perspectives of deviance: social control theory and subcultural deviance theory.

Social control theory assumes that individuals have a default propensity for committing deviant, including criminal, acts due to a lack of norming bonds to conventional society (Hirschi, 1969). Deviant individuals lack ties to conventional institutions, such as school, and social groups such as family. Hence, their relationships become "cold and brittle" (Hirchi, 1969:141). This description elicits the image of an extreme deviant such as a drug abuser estranged from family and friends. Their relationships are unreciprocated, shorter in duration, less cohesive and intense, less dense, and smaller, all due to the lack of the social skills necessary for maintaining stable relationships (Hawkins and Fraser, 1985)(Gainey 1995).

Some recent studies seem to support the alternative, subcultural deviance theory, which posits that deviant groups look quite similar to non-deviant groups with ties that are just as, if not more, intimate. The difference lies only in the context or activities of the groups. That is, the deviant behavior expands and persists through peer reinforcement according to social learning theories (Akers, 1977) or differential association (Sutherland, 1974). Drug use studies by Hawkins and Fraser (1985), Giordano et al (1986), and Kandel and Davies (1991) conclude that sub-cultural deviance better supports their findings than social control theory despite minor differences between drug using and non-drug using groups. Other research, however, finds subtle structural differences between the drug using and non-using individuals while gross measures of stability and intimacy seem to show little or no difference (Krohn et al 1988)(Gainey 1995).

Alternative, psychological theories are also gaining empirical support. These theories posit deviance as a result of individual decision-making behavior: the lack of self-control (Goffredson and Hirschi, 1990) and the inability to foresee future, negative consequences of current deviant behavior (NIDA 176, 1998). Macro-sociological effects of population, specifically the relative cohort size à la the Easterlin hypothesis (Easterlin 1987), are known to impact deviant behavior including drug use (Elliot et al 1988)(Lee 2001)(Savoleinen 2000). Between the psychological and macro-sociological perspectives lie a host of interaction theories that have often been used to explain individual level social behavior and explicate deviance theories. Balance theory posits that local relationships conform to reduce dissonance induced by certain configurations of affect (Heider, 1958; Homans, 1961; Newcomb, 1961; Thibaut and Kelly, 1959). Homophily predicts the formation of relationships between individuals who share common values, attitudes, or demographic attributes (Laumann, 1973; McPherson, 1992; Wellman, 1982).

Methodology

The testing of these theories continues in an effort to determine the accurate paradigm for understanding drug use, specifically, and more generally, deviance. However, due to data collection constraints, a synthesized experiment, examining all levels of deviance, is virtually impossible. National level data necessary for a complex model of deviance, in this case drug use behavior, are incomplete and require some modifications in order to be incorporated into any coherent model.

A set of such ego-network data is available in the 1985 General Social Survey (or GSS). However, this survey lacks data on drug use. The National Household Survey on Drug Abuse (or NHSDA) contains several thousands of drug use data for 1985 and an order of magnitude more across all years that the survey was administrated. Multiple imputation techniques (Rubin, Schafer) will be used to create a statistical inference model between network data in the GSS and drug use data in the NHSDA using variables common to both surveys such as demographics. Preliminary results have shown that network correlates do exist for drug use as demonstrated by prior network and drug use research (Krohn et al, 1985)(Gainey, 1995). Census data provides cohort size data which have been used to calculate relative cohort sizes. Relative cohort size has been shown to predict drug use in the NHSDA (Lee, 2001) and the NLSY (National Longitudinal Survey of Youth)(Elliot, et al 1988). Psychological data, informative of individual decision-making behavior relevant to deviance, are not available.

Evolution of ego-networks is inferred from cross-sectional data. Trends in GSS network variables provide a basis for network evolution while imputed drug data informs the distribution of drug use for the evolution population. The evolution process is portrayed primarily by a series of trajectories in multiple phase space graphs. The dynamics of drugs use and disuse is dependent on the relative sizes of the at-risk age groups. That is, it matters what year we decide to place the evolution. Youth cohorts in the early 80's are particularly sensitive to the Easterlin effect, which posits that cohort larger than preceding cohorts are subject to various forms of economic and social strain.

The competing theories of deviance are tested under this model. Current findings echo those of the extant literature. Social control is exerted through the structure of the local network while deviant subcultures are indistinguishable from mainstream, non-deviant groups.

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Simulating Extreme Collaboration: a Case Study

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Understanding how technology can aid cooperation has always been a great challenge in the Computer Supported Cooperative Work (CSCW) field. In fact, studies of collaborative work in a naturalistic setting have been used to understand characteristics of actors involved in cooperative work, and their interactions and activities within their shared environment. Understanding this type of "real-world" cooperation is fundamental for designing innovative solutions to support cooperative work. Such solutions are not limited to groupware tools, but also include new cooperation configurations (such as designing groups and their environments) and communication devices. The deeper our understanding of the collaborative process, the better that technology can be designed to support and improve it. Our ultimate goal in understanding cooperation is to improve the usability, and adoption of groupware systems.

Collaboration has many aspects. In this paper we focus on one type of collaboration, where group members meet face-to-face, co-located in the same room, and work synchronously. We have chosen a unique face-to-face collaborative setting that we refer to as ***extreme collaboration***, where a physically collocated team uses computer technologies, an innovative design process, and room environment to streamline communication and information flow. Why have we chosen to study this group? Recently, there has become an interest in studying the effects of placing project teams to work together on an entire project in the same meeting room. Rather than gather teams exclusively for status meetings, the idea is to have teams working together synchronously in all phases of the project. Some results suggest that such environments can lead to increased productivity [Teasley et al. (2000)]. The study of this team found that the time to produce completed missions proposals has dropped dramatically by having the team work together in the same room, compared to previous distributed work. Quality is seemingly unaffected.

The team we have modeled works at NASA's Jet Propulsion Laboratory (JPL). In April 1995, the Advanced Projects Design Team, known as Team X, was formed to serve as internal consultants to NASA in designing new missions proposals. The design proposal defines all aspects of a mission: how the science requirements will be fulfilled, which telecommunications devices to use, how much power and propulsion is needed, what information will be transmitted back to earth, and so on. Team X is composed of sixteen members who are engineers with expertise in a particular subsystem for space mission design, such as power, thermal, or telecommunications systems. There is also a team leader and a customer. Each member sits at a table with computer terminal. The leader stands either at the front of the room, or moves about. Technologies are used to support their collaboration including three public displays, databases from past missions as a memory aid, an orbit visualization program, and a simple publish-subscribe system of networked spreadsheets to exchange information.

Fieldwork has been conducted with this team in order to understand its collaborative process. Our goal is to model certain elements in this collaboration in order to understand the particular role that each element plays, e.g. seating position. The teams were observed over a period of three months, with meetings of one to three sessions per week, three hours per session. Forty-two hours of observation were made, where the observer (one author) took notes on conversations, watched team members working, asked members about their work, and coded the group activity in real time, focusing on sidebar conversations. In addition, seventeen in-depth interviews of about one hour each were conducted with team members and others related to the team.

The fieldwork observations revealed that during their design sessions, the group members move continually between separate individual subsystem work, small group work, and orchestrated entire team work. They also selectively monitor, access and filter various sources of information: sidebar conversations, public conversations, public displays, the team spreadsheet, the team leader, the customer, the neighbor's screen, and one's own spreadsheet. The team members use all the information available to them in the room in order to guide them in deciding whether to do individual work, small group work, or collective group work. The room configuration, known interdependencies between subsystems, and the ability to selectively monitor information, aids the entire group in recovering errors and in joining relevant sidebars.

Modeling the extreme collaboration process

Extreme collaboration is a very complex process; where *heterogeneous* (different skills and roles) *agents* (actors (engineers, leader, customer)), who are *dynamically organized* into subgroups, *adapt* their behavior (individual work, within sidebars, moving, overhearing), *monitor* information selectively, make *feedback* continuously and in an *unpredictable* way, improve mission design, solve problems, and adjust costs. We will investigate the new emerging theory on complexity [Axelrod and Cohen, 2000] and its use for CSCW field by applying a computer simulation approach to extreme collaboration in order to provide more quantitative and objective results on cooperation. There is a great recognition that computer simulation, especially agent-based simulation, is necessary for complex systems. Biology, chemistry, and physics, have largely benefited from simulation. More recently, social applications are using simulation.

- In our case, we are designing and developing an agent based simulator in order to:
- Have a virtual extreme collaboration environment where we can evaluate (run and compare) different cooperation scenarios (real and hypothetical),
- Study the relationship between the spatial configurations and group activities in monitoring various sources of information and recovering errors.
-

Our computer simulation approach would assist CSCW designers in their design choices, by maintaining the best scenarios and eliminating, for example, "catastrophic" combination of parameters and values. It would also be useful for defining strategies for integrating solutions into organizations by giving ideas on what to change first and its probable consequences within a future context. Our findings would contribute to the design of CSCW solutions by providing a "manageable" evaluation of great number of different configurations.

In the field studies, we found that monitoring the environment: 1) helps team members to *recover from errors* in using software, and 2) it provides awareness of *sidebar* discussions so that team members know where they need to contribute their expertise. Consequently, we are building the simulator with the purpose of simulating two "cooperation patterns" important in extreme collaboration, and in cooperation in general: sidebar monitoring and error recovering.

Our first purpose is then to understand the sidebar formation, its influence on the performance of the process of mission design, and to compare a collocated vs. distributed context. A sidebar is a dynamic subgroup. It is a set of two or more participants (a subgroup) joining together to solve an emerging problem. These participants are not necessarily in the same place in the room. Their conversation is not private and can be heard by every one in the room. The leader or any other participant can initiate a sidebar. According to the topic of a sidebar, new participants can join it (even through monitoring it) or leave it. Consequently, a sidebar can be characterized by its location in the room, its topic of conversation, its duration, its size, and its members. During our simulation, studying the influence of such parameters and others (actors, activities, interdependencies) will give us an in depth understanding of:

1) sidebar formation based on monitoring information content (how, when and why: explicit request, cocktail party phenomena, overhearing, sharing, etc.),
2) space and sidebars (influence of space(same or distributed location) on its formation, its duration)
3) sidebar as a pattern of communication (dynamic sub-network) in the group to measure the degree of coupling between subgroups and participants which will be useful for designing virtual teams involved in extreme collaboration across distance,

Errors are characterized by their type, occurring time and source subsystem (i.e. which , where and when an error occurs). By running a simulation where room configuration and group interdependencies are known, several measures concerning the error recovery process would be computed:

1) propagation depth and duration: how far errors propagate and how long they stay before being found out,
2) when and how errors are caught: by whom(any member, the leader, one sidebar), and from which source of information(e.g. :the spreadsheet, the public displays contents, etc.)

By changing the room configuration, spatial arrangements and group distribution, etc. we would study the influence of space, time, and communication artifacts in the environment on error monitoring by the group.

We are using object-oriented and agent-based methodologies for designing and developing an Extreme Collaboration Simulator. We applied a bottom up approach to model our team work. We extracted collaboration scenarios to simulate sidebars as well as error catching.

Overview of the model: specifications

We are designing a computer simulator, which is a virtual environment:

- Taking into account the actors, their activities and interdependencies as well as the environment in which they are collaborating including the collaboration artifacts.
- Able to mimic the observed team collaborating,
- Able to support experimentation of new, "hypothetical" scenarios,
- Generic tool offering reusable modules, which may re-used by other organizations and collaborative situations.

We are using an Object-Oriented approach to design and develop our model and simulator in an iterative way. The main classes of our object class model are *member, environment, sidebar, and error.* We are simulating the sidebar conversation based on the cocktail party phenomenon (Cherry, 1953), where names, roles, or keywords related to interest that are overheard, trigger group members to join the sidebars. Thus, in our model, the *member* class refers to any human actor in the group. It is characterized by the *name*, the *role* (e.g. leader, customer, heat engineer, thermal engineer), the *seating position* (where his/her terminal is set and is supposed to be unless (s)he has moved to a sidebar), a *set of specialty knowledge* “keywords” for which one member may react (e.g. heat, cell, thermal, temperature). We finally add a *set of sidebar topics* of which one member is aware. So, during our simulation, as soon as a sidebar is made, the sidebar topic set of each member is updated according to what he is hearing and seeing.

The *environment* class includes mainly a description of the communication artifacts used by the group (e.g. location of the public display and its content). It is intentionally separated to support independent analysis of the environment factors and to enable future additions of new factors (e.g. new collaboration artifacts, level of noise in the room).

The *sidebar* class includes the *beginning time*, the *topic* of each sidebar (whose value may be any of the all known specialty keyword sets characterizing the members), and the *initiator* (which may be any member of the group asking for information about the previous topic). *End time*, *location*, and *set of its participating members* are also in the sidebar class.

We model also an *error* class as a separate object class. This allows us to keep track of each error separately and to easily associate group members with errors. Each error is characterized by: its *beginning time* (when it occurs), the *initiator* (by whom), its *topic* (e.g. the error topic may be *heat error*, *cell error*), *end time* (when the error is caught), *propagation depth*, and an *error users list* (where is kept the list of members who used the related information).

We will begin our study focusing on sidebars first, and then errors separately.

Simulator input

At the beginning of a simulation run, two input files will be setup:

1. Group properties file including, for each member of the group: *role*, *seatXPos*, *seatYPos*, *specialtyKnowledgeSet*
   According to the seating position of every member, the neighbor of everyone is set.
   When seating position Values are out of the range of the room size, they refer to a spatially distributed team.
2. and Sidebars file including a series of “events”(sidebars occurrences) characterized each by: b*eginning time*, *initiator*, *topic*,

According to the BeginTime, one or more sidebars may be run on the same time. This enables us to test several scenarios with one or more sidebars. Environment attributes (room size and displays positions and contents) are set to default values. Size of the group is set to 18 as default value (which is the real size of teamX).

Simulation process

In all cases, both of the input files have to be filled out with the adequate values corresponding to the scenario to be simulated. The sidebar events (their occurrence) will generate the dynamic process of group interaction: As soon as a sidebar is initiated, one or many members in the group will react (e.g. hear, answer, move). As the simulation progresses, communication between actors and movement across the room will be shown. The simulator will provide an overview plan visualizing continuous communication, movement, and physical settings. Graphs will trace the number of sidebars over time. For each sidebar, duration, size over time will be computed. Additional representations of events and results may be added. Simulation parameters and their values will be saved into files for further statistics analysis and comparisons.

Error simulation parameters and process

To study errors, we will reason by analogy to sidebar study. For sidebars, the simulation is launched by the event of ***initiation*** of a ***topic*** by one actor at a certain date . It evolves according to the environment and state of agents in it: information is “propagated” and the cooperation in the group emerges. For the errors, we will consider as input events of errors appearance: an error topic will be done by one actor at one moment. Then in the simulator, we will follow the path of the error propagating to the rest of the group as this error will be thought of as being a “normal” information exchanged and integrated in subsystems until it is (or its erroneous consequences are) caught. During the simulation, each subsystem where the “error message” is used will be added to the Error users’ list. Consequently, at the beginning of a simulation run, we need the same things for sidebars except that the sidebar input file is replaced by the error input file. This latter includes a series of “events”(error occurrences) characterized each by: *beginning time*, *initiator*, ***errorTopic***,

Simulator output

At least three output parameters are caught from the various simulation runs: error duration, propagation depth and error “propagation depth” before it is caught. The simulator will also draw a map of all communications among actors during one error propagation (from its occurrence until it is caught). These output parameters, correlated to input one, would be subject for further analysis to look how environment and group properties affect errors recovering.

Our simulator is being developed using the SWARM[10] platform (developed by the Santa Fe Institute). The simulator is under construction. We expect to soon report relevant information about the spatial configurations on sidebars formation, the

[10] www.swarm.org

degree of coupling between team X members, and the errors recovering process (in terms of their sources, propagation depth and duration, diagnosis by the group or sidebars).

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Can We Control Information Free Riders?
Analyzing Communal Sharing Norms via Agent-based Simulation

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1 Introduction

In this paper, we will discuss a communal sharing norm about information properties. By the communal sharing norm, we means that people share their resources together. Such sharing of resources plays an important role as a reciprocal norm in human behaviors. Communal sharing encourages us to maintain human relations and closeness [1]. The resources for communal sharing include money, physical properties, services, love, and social approval [2]. Among them, the role of information resources has become important in recent net-based societies. The characteristics of the imformation resources are quite different from the physical ones. Thus, the communal norm sharing behaviors might be different from the traditional ones. This paper focuses upon the birth, growth, and stability of communal sharing of information resources in a society.

To carry out the study, we adopt an agent-based simulation model. Agent-based models can usually find macro phenomena from the interactions among agents. Although a model designer knows functions and natures of agents, (s)he doesn't know what phenomena would happen as a whole during the simulation. Contrary, in the following aspects, our agent-based model is different from conventional macro models to analyze social phenomena.

Our approach is characterized by the facts that: (1) the simulation model consists of heterogeneous agents, which have functions of decision-making and communication; (2) we observe emergence of social phenomena as a result of optimization of a social macro index by genetic algorithms; and (3) we analyze the emergent phenomena and characteristics of each agent. In this paper, we utilize our artificial society simulator TRURL based on this framework to analyze the communal sharing norm about information resources.

2 Aritificial Society Model TRURL

We have developed a novel multi-agent-based simulation environment TRURL for social interaction analysis.

- The agents in the model have detailed characteristics with enough parameters to simulate real world decision making problems.
- Instead of manually changing the parameters of the agents, we evolve the multi-agent worlds using GA-based techniques.
- Each agent exchanges knowledge and solves its own multi-attribute decision problems by interacting with the other agents

Artificial society TRURL generates many societies with genetic algorithms, then it can recreate a similar society in terms of a social macro index. Each society is represented as genes of predetermined parameters of agents who constitute those societies. Those societies are evaluated with a social macro index after interactions among agents. Selection, crossover, mutation and reproduction are repeatedly carried out. The social architecture is gradually organized by a social index as an objective function.

Social network researches have shown that the process of communication and opinion formation in a community can be measured with a socio-metric. If this socio-metric is the objective function of the artificial society, we can recreate the same phenomenon as a real society[5].

3 Experiments

Research in the literature have shown that (1) a communal sharing norm is spontaneously stabilized in a society, (2) however, free riders break the sharing norm of resources. These results only consider the sharing norm of *physical resources or properties.* In this section, we describe experiments whether the sharing norm of information properties is stable or not. We constitute three kinds of societies in the following. Then we carry out experiments about free riders, intolerants agent, and the information gap.

1. Face-to-Face communication oriented society (FFS)
   The communication among the agents are constrained by both the physical and mental coordinates. They interact with physical and mental neighborhoods. The ratio is parameterized.
2. E-Mail oriented society (EMS)
   The communication among the agents are constrained by the mental coordinates. In this society, agents interact each other one by one at each step.
3. Net-News oriented society (NNS)
   NNS is an extension of EMS. It has a virtual whiteboard at the center of The world. Agents in the world send messages to the whiteboard, and the whiteboard distributes the messages to all the agents. The credibility value of the messages is the same as the one of the senders.

3.1 Emergence and control of free riders

Figure 1 shows the change of the average values of the message-send-gene of all agents in FFS. Y-axis is average message sending probability. X-axis is the amount of communication. Sending probability decreases slowly. It means that free riders emergent in FFS. In FFS simulation results, we have also found the same phenomenon in EMS. An agent loses the energy for communication gradually, while it gets the energy for worthy information. The free riders can live forever, because they do not send messages and only gets information in the world. Therefore, the amount of sending messages decreases, and agents who have the sharing norm lose the energy, because they cannot get worthy information, though they expect rewards as sharing for sending messages. Eventually all of them would go away.

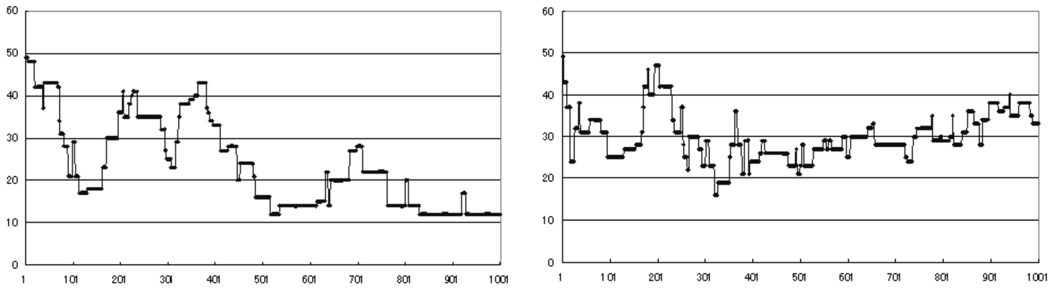

Figure 1: The change of message-send-gene and the effect of tolerant agents. Left is the increase of free riders. Right is the supression of free riders (1000terms, Average of 30agents/society)

We extended the model not to send any messages to the free riders. The result of the experiment is shown in Figure 1. Free riders cannot get more information, and they lose their energy. As a result, the decrease of message-send-gene is controlled in the society. So existence of intolerance agents can control free riders without explicit punishment.

3.2 Information Gap

The information gap among agents and the efficiency of information acquisition can be examined using Inverse simulation of TRURL, The information gap can be measured with Gini index. Gini index is a sample statistic in economic categories and represents a income gap. The larger Gini indedx values means the more income gaps, that is, there are the more difference of incomes among the rich and the poor.

$$Z_{Gini} = 1 - \frac{\sum_{i=1..N}((2\sum_{k=1..i} E_k - E_i)A_i)}{(E_{tot}A_{tot})}$$

sort data: $Ei/Ai > E_{i-1}/A_{i-1}$, A_i: "people" (population in $group_i$), Ei: "wealth" (the amount of information in $group_i$), $A_{tot} = \sum_{i=1..N} A_i$, $E_{tot} = \sum_{i=1..N} E_i$

We simulated 20 societies with Gini factor as an objective function. The results are that maximum Gini factors are 63% in FFS, 54% in EMS and 48% in NNS. This means $FtoF > Email > Netnews$(Table 1).

Table 1: The gap and nature of information rich persons

	FFS	EMS	NNS
Max Gini factor	63%	54%	48%
Sending probability of the rich	0.75	0.63	0.20
Receiving probability of the rich	1.0	0.94	0.92

Netnews society has less information gap than the other societies. We have observed the genes of the information rich agents in each society. In FFS, the rich agent is to send many messages (Probability: 0.75) and to read them frequently (Probability: 1.0). In NNS, the rich agent is to send few messages (Probability: 0.20) and to read them occasionally (Probability 0.92).

This results suggest the followings: In FFS, the active agent, which gathers information by itself sends the information and listens to other agents frequently, can become the information rich. In NNS, the Net surfer agent, which sends few messages can become the information rich. It reads information on the Net instead of gathering information spending costs, EMS is seated at the midpoint. In addition, we used the following objective function for the simulation. $\sum_{i=1}^{n} m_i \quad : m_i isactionenergyofagent_i$

This maximizes the amount of action energy, which is the difference between information value and gathering cost. It indicates that the agents communicate their information efficiently and represents the efficiency of the society to gather information. The result is shown in Table 2.

Table 2: Difference of energies in each society

	FFS	EMS	NNS
Max energy	54unit	77unit	165unit
Max energy ratio	1.0	1.4	3.1

NNS has the ability to gather information 3.1 times as much as FFS. Although the information rich agents exist in NNS, the information gap is less than other societies.

4 Concluding Remarks

This paper has described agent-based simulation and their experiments about a communal sharing norm on information properties. We have observed the emergence, collapse and control of norms in FFS, EMS and NNS. From the experiments, we suggest that (1) NNS has big communication ability, (2) free riders emerge in any societies, (3) an intolerance agent can control free riders, and (4) the information gap in NNS is the smallest.

From the viewpoint of the communal sharing norm, the expermental results have implies the following items: Information property has a different nature from physical resources in terms of sharing. Sharing and distribution of information don't mean to reduce their property values. Digital Divide might be one of these phenomena. So the results may persuade to change a definition of a free rider in NNS.

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Learning Economics Principles from the Bottom
by both Human and Software Agents
- Outlines of U-Mart project –

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Introduction

The Complex behavior of market economy, typically observed in financial markets, is not fully explained by conventional economic theories. A new approach to this problem is an artificial market, which enables us to carry out computational experiments on virtual markets using agent-based simulation[1][2].

Studies on artificial markets have achieved a variety of interesting results. However, they also clarified the difficulties peculiar to the agent-based simulation approaches, such as that i) Researchers from different fields need to cooperate due to the interdisciplinary nature of this approach, ii) It is a very tough issue to design a model which combines the complexity to imitate real markets and the simplicity to enable us to carry out computational experiments, and iii) Researchers need to share common understanding on experimental configurations and results which are much more complicated than conventional theoretical models.

U-Mart [3], [6] is a research program to address these problems of artificial market studies. We have developed several simulation toolkits, called U-Mart systems, to provide a test-bed for researchers and students from economics and information sciences to carry out experiments with common understanding. We are now promoting diversified researches on markets by opening this system to public. Such an open-minded approach to deploy a testbed has been already successful in Robo-Cup project [5]. We would like to conduct the U-Mart project as a *Robo-Cup in Economics*.

Principles of the U-Mart Project

The objectives of U-Mart are summarized as follows: i) to develop a common testbed for interdisciplinary researches for both economics and multiagent systems; ii) to provide common gaming and simulation environments about market mechanisms, iii) to deploy multiagent simulation research toolkits about virtual markets, and iv) to develop practical educational environments about market mechanisms and economic simulations for university level students. In the following subsections, we will describe the trading in U-Mart and the system architecture.

In the U-Mart system, *future goods* in real markets are traded in a virtual market. Futures trade is a trade to buy and sell goods at a certain point of time in the future (due date). The price of a future good is determined as an actual market price (spot price) at the due date and is indeterminable before the date. In futures markets, it is also allowed to enter a reverse transaction before due date to make settlement with the balance between the futures buying price and futures selling price. U-Mart deals in stock index futures. Stock index is commonly used to see the stock price level and is defined as a weight average (or a simple average) price of listed stocks. In stock index futures, stock index is considered as a price of a fictitious good and traded in the futures market.

Of course, in U-Mart, the actual good cannot be obtained even at the due date because it is fictitious. Therefore, members of the market make settlements with the balance between buying or selling prices and the spot price at the due date. This method is called "closing out positions". In U-Mart, a stock index future in the real world is traded fictitiously in a virtual market. And we have a plan that U-Mart is operated in parallel with real spot markets. When the plan would be available, it would be possible in theory that the participants of U-Mart trade in real spot market or that traders in real spot market consult U-Mart, but it is not much practical. The strategy we take allows the market simulation environment to reflect the complexity of real markets, and enables it to form the independent price of the corresponding goods.

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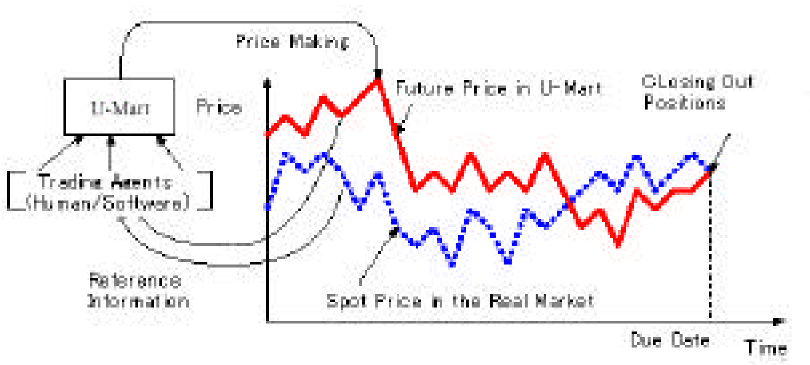

Figure 1. Outline of U-Mart Artificial Market System

The original system of U-Mart has been developed as a client-sever system to exchange information, such as buying and selling, via the Internet using specific protocols implemented on the TCP/IP. A sever, which imitates an 'exchange', accepts orders from clients, determines prices, matches buying and selling, and manages clients' accounts. Each client obtains the information, such as market performance, from the sever and places order under its own decision. In the U-Mart system, human agents, as well as machine agents, are allowed to participate in market experiments. The participation of both human and machine agents brings the variety and reality to the virtual market.

The activity of U-Mart project are (1)The design specification of a transactions server adjusted, (2)defined the protocol (SVMP: Simple Virtual Market Protocol) for realizing futures trading by the Internet, (3) Development of U-Mart server which fulfills the specification of SVMP and the software agent used as a prototype sample, (4) Development of the transactions interface for human trader, (5) Development of courseware for the student in a graduate and undergraduate school for studying development of machine agent and the foundation of market transactions.

We have already conducted many open experiments and lectures to a student using these kits. Although only the agent of a simple decision-making algorithm (for example, random, trend and anti-trend) existed at the beginning, in order to participate in a open experiment, development of various agents is furthered, such as time-series analysis (technical analysis) , Genetic Algorithms (GAs) and Artificial Neural Networks (ANNs). And some research efforts are bearing fruit from software engineering or the knowledge of artificial-intelligence research[4].

Experiments of U-Mart with Only Machine Agents

The objectives of the experiment are: to investigate variations of trading strategies and development methods for software agents, and to verify the actual behavior of market simulation among independently developed agents. Since it is the first public experiment for us, we limit the entry only to software agents. No human agents are allowed. This is the reason that we name it "Pre U-Mart 2000", which targets only a part of U-Mart conception. The participants have received an agent development toolkit of U-Mart system in advance. At the occasion of the experiment, Pre U-Mart 2000 committee set up a server machine, and the participants run agent programs on their note PCs connected to the server via the Ethernet. The participants and the audience can watch the progress of the experiment through a video projector. We tested the operation of the system on the first day of the symposium, and conducted the experiment in the second day.

Eleven teams participated in the experiment, seven from computer science (CS) backgrounds and four from economics (EC) backgrounds. Each team was assigned a quota of five agents. We have conducted the experiments twice with different spot price series data. The numbers of attended agents are 47 for the first round and 43 for the second round. Not every team uses its full quota of the five assigned agents. Eleven teams participated in these experiments and the variety of the agents exceeded our expectations. Deals tend to fail when agents with similar behavior make similar decision. To achieve deals, agents that place random orders need to be introduced on the market. In our experiments, the prices have been formed between the varied agents without random agents.

In the first round, the heavy rises and falls are repeated at the beginning because of excessive limit order and market order combinations. The second round shows only a few times of rapid price movements. Figure 2 shows the transitions of price and trade volume of first and second round.

Experiments of U-Mart with Only Human Agents

Heavy rises and falls have resulted at the beginning of the experiments with machine agents. What happens if more sophisticated human agents deal in this virtual market? The U-Mart system can answer this question since it is designed to allow human agents to participate in market experiments. To describe the behavior of virtual markets constructed by human agents, this subsection introduces the experiments conducted at Kyoto University. In this experiment, a machine agent has made the best profit between one machine agent and seven human agent (including one faculty), and three students go into bankruptcy

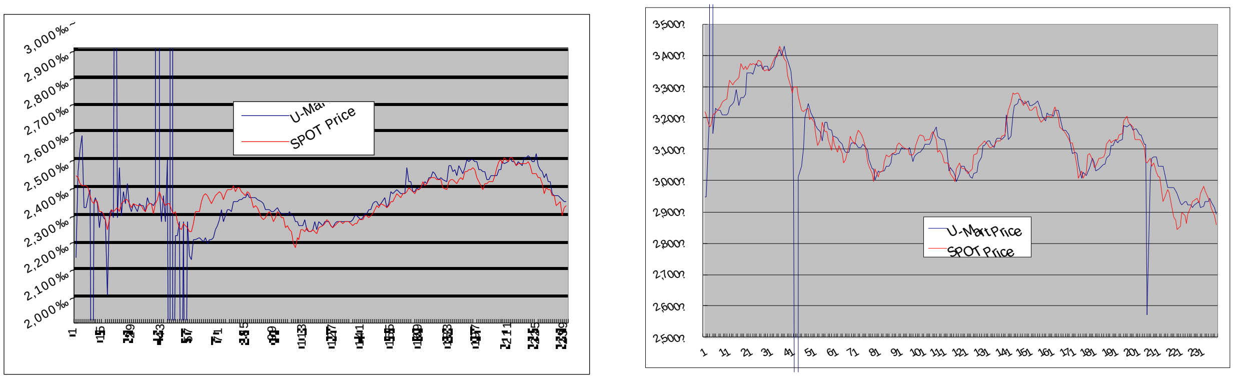

Figure 2. Prices and Traded Volumes for the 1st. Round and 2nd. Round

According to the students' reports after the experiments, the bankrupt students predict down-trend of spot price in long-term. They focuses on buying initially and continues selling after that, then go into bankruptcy along with the up-trend of spot price. On the other hand, the profited students respond to short-term price movements. They make small profits with a general strategy, which is to sell when price increases and to buy when price decreases. They maintain the stable position.

The experimental results show remarkable differences on behavior of human agents and the present machine agents. Human agents not only make technical analysis of short-term price movement, but they predict long-term market trend and conceive a strategy based on impression. Although the machine agent has made the best profit in this experiment, it highly depends on contingency in connection with the used spot data and the strategies of human agents. From now on, more experimental cases need to be accumulated to analyze U-Mart as a market and to examine differences between human and machine agents. We will also look into the availability of this system as an educational tool.

Conclusion

In this paper, we described the basic principles of the U-Mart project and its open architecture, and have reported on the experiments of U-Mart system, conducted with machine agents and/or human agents. The results of experiments have shown the promises to construct a variety of machine agents and clarified the strategic differences between human and machine agents. We will continue this study program forward by integrating the knowledge obtained from both type of agent simulations. It is also interesting that the results indicated the usefulness of the U-Mart system as an educational tool for both economics and information science. And we are already preparing some kits include U-Mart system for education and is used at the lecture.

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