INFLUENCE OF NEIGHBORHOOD AND SELF REORGANIZATION IN NETWORKED AGENTS

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Abstract: In a network graph in which nodes represent agents and edges represent "can work with" relationships, coalitions form. Such coalitions satisfy the skill set requirements of a task while still obeying partner requirements. Agents composing a coalition must form a connected subgraph in the network graph. There is no centralized control, and agents are free to propose any coalition that satisfies both the skill set and partner requirements. In this research, strengths of various coalition formation strategies are compared with respect to both success and profit. To determine the quality of the solution and for comparison purposes, we temporarily remove the restriction that an agent can belong to a single proposed coalition and that a task can be proposed by a single coalition (i.e. hedging environment). In addition, agents are given the ability to dynamically reorganize their partner connections in an attempt to improve utility. Agents employing egalitarian, intelligent and inventory reorganization are compared with agents employing structural and performance reorganization.

1 INTRODUCTION

We model the coalition formation problem as a network graph in which nodes represent agents and edges represent a "can work with" relationship. Each agent possesses a single primary skill. Tasks require a set of skills that must be present in the coalition for the duration of task execution. Coalitions are restricted to sets of agents linked via edges.

Reorganization is viewed as the mechanism enabling individual agents to change their connections dynamically without explicit external commands (Marzo Serugendo et al., 2005). This behavior can be generated in multi-agent systems in several ways (Barton and Allan, 2008; Gaston and Jardins, 2005; Thadakamalla et al., 2004). This paper performs a comparative analysis of various strategies of task selection and coalition formation.

Some strategies introduce specialist agents to the organization (Hoogendoorn, 2007) to manage each agent's connections. Yet other methods, such as organizational self-design (Kamboj, 2009), achieve reorganization by dynamic spawning and merging agents. In our model, we use autonomous agents to improve and analyze reorganization.

2 RELATED WORK

In Abdallah and Lesser's work (Abdallah and Lesser, 2007), agents organize themselves in an *overlay network* in which agents only interact with neighbors. Similarly, in our method, agents reorganize. However, Abdallah and Lesser restrict their problem to that of task allocation (assigning one agent to do a task) rather than coalition formation. Gaston and Jardins (Gaston and Jardins, 2005) consider social networks and task formation with multiple skills per task, but do not have varying agent types.

In Barton and Allan's work (Barton and Allan, 2008), self-organized social networks under changing resource requirements are considered. Edges in the social network can be modified by either adjacent agent. Such modification is termed *rewiring.* However, the results lay at a low range of efficiency and performance, typically less than 45%. In our research, we extend these results by showing that the efficiency/performance is often dictated by the maximum connections each agent maintains.

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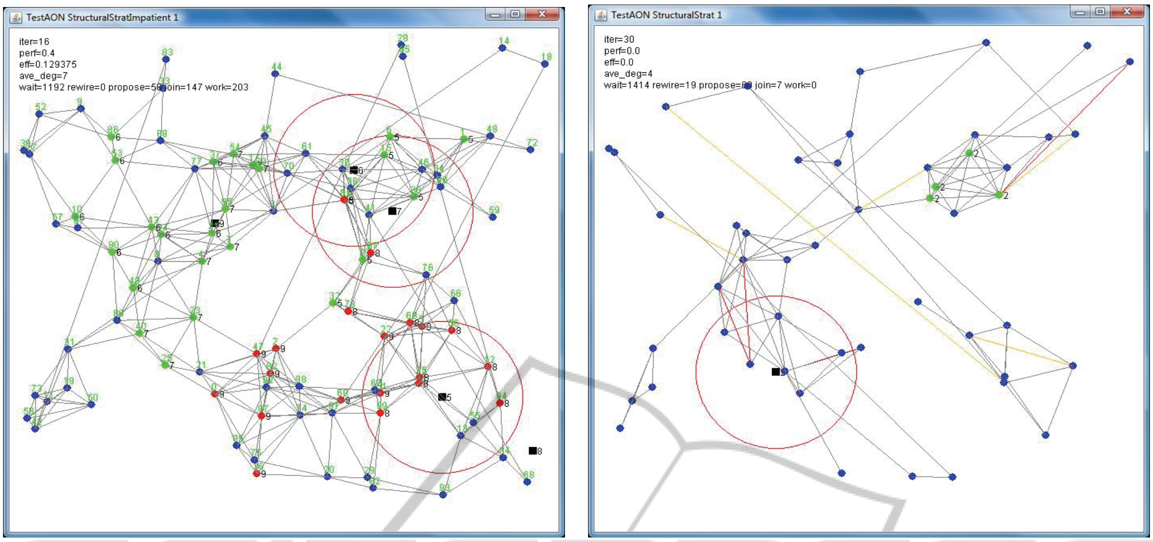

a) b)

Figure 1: Networked agent simulation: a graphical representation of the networked multi-agent system. Each node represents an agent while an edge represents a relationship which indicates "can work with". Nodes in blue are uncommitted agents which are available to form a coalition or reorganize themselves in a better neighborhood. Nodes in red are committed agents which are executing a task in a coalition (a). Nodes in green are committed agents in a partially formed coalition for a given task. Edges in red are newly created relationships as a result of reorganization (b). Shaded edges represent an abandoned edge due to reorganization.

3 SIMULATION

In this research, our goal is to determine strategies which improve the success of a distributed coalition formation network. Tasks have equal utility and are generated at regular intervals during the simulation.

We define *success-rate* of an agent as the fraction of successfully completed coalitions divided by the total number of coalitions joined.

In our model, agents first consider joining coalitions to which their neighbors belong (partner requirement). Here, *neighbor* means a node connected to an agent by an edge.

The state of an agent, based on the coalition perspective, is as follows:

- *active* - executing a current task
- *committed* - has joined a coalition that has not begun execution
- *uncommitted* - agent which can propose a new coalition or join a coalition proposed by a neighbor

The set of agents that an agent can see in following paths of a predefined length is termed *communication depth*.

4 AGENT TYPES

4.1 Random Agents

Random agents are a primitive type of agent that join coalitions (if possible) and otherwise propose. No specific criterion is used to select the task to join/propose.

4.2 Strategic Agents

Strategic agents select the coalition to join based on a blend of (1) the coalition with the highest percent of committed agents and (2) the coalition for which peers (i.e. neighbors of neighbors) have the best match with skills needed for the coalition. If the agent is not satisfied with choices for joining a coalition, the strategic agent can then propose a new coalition, selected based on whether its peers have a sufficiently high chance of satisfying the necessary criteria. As a last resort, the strategic agent can randomly propose a coalition.

5 REORGANIZATION

An agent has the ability to remove an edge between it and its neighbor and create a new edge with an agent that is not a current neighbor. This is termed *reorganization*. We study five types of reorganization: **performance reorganization** (Gaston and Jardins, 2005), **structural reorganization** (Thadakamalla et al., 2004), **egalitarian reorganization**, **inventory reorganization**, and **intelligent reorganization**.

Table 1 summarizes the parameters of each reorganization type in the connected agent network.

Table 1: Summary of each reorganization strategy.

Reorg.	Trigger	How Selected	Can refuse
Performance	prob 1/|A|	performance	no
Structural	prob 1/|A|	most connections	no
Egalitarian	prob 1/|A|	fewest connections	no
Inventory	prob 1/|A|	needed skill	no
Intelligent	poor performance	current skill demand	yes

6 ENVIRONMENT

6.1 Hedging Environment

In our model, we compare the effects of allowing agents to commit to multiple coalitions (that are not yet executing), and we allow multiple possible coalitions to be associated with the same task. The tradeoff in this environment is the balance between a higher number of successful coalitions and the cost of discarding unsuccessful coalitions.

7 EMPIRICAL EVALUATION

In our first set of experiments (Figures 2-3), each random, strategic or hedging agent is connected with the same number of neighbors (number of connections). No reorganization is done here. In our second set of experiments (Figures 4-5), the behavior of hedging agents employing five different reorganizations are analyzed.

Consider Figure 2. We use the term *saturation point* to indicate the point at which an agent achieves a .9 (90%) performance-rate (in the tests). In the hedging environment, agents reach the saturation point at 10 connections. Strategic agents require 18 connections to achieve their saturation point. Random agents require 20 connections to achieve their saturation point.

Figure 3 shows the corresponding profit earned by each agent simulation. Interestingly, in the hedging environment, the profit degrades from its maximum value when the number of connections is more than 34, due to the higher communication cost and insignificant improvement in reward.

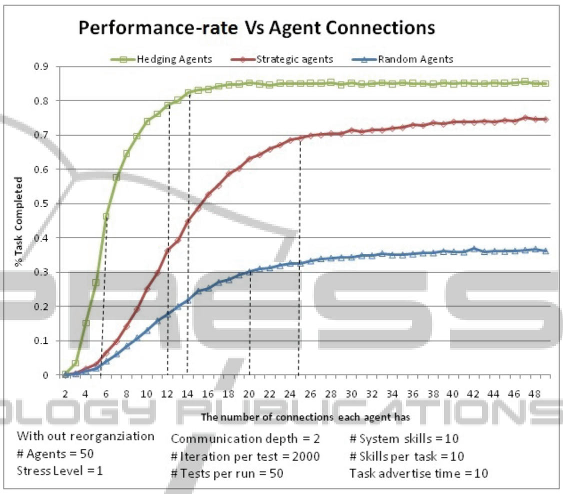

Figure 2: Performance-rate Vs Agent Connections.

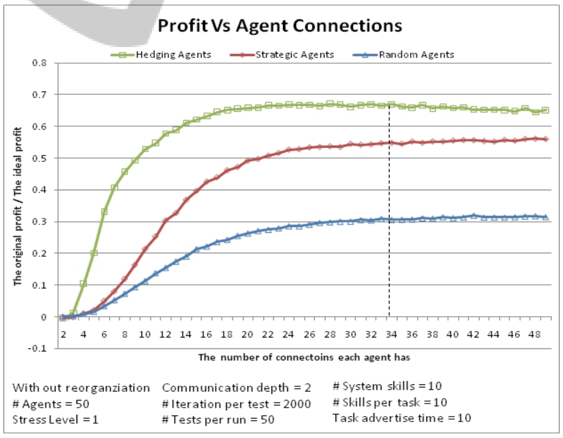

Figure 3: Profit Vs Agent Connections.

Agents employing reorganization give us the opportunity to understand the effects on the performance-rate, and interestingly, the dilemma of society, a tragedy of commons (Axelrod, 1997).

Figure 4 depicts the performance-rate of the hedging environment with five types of reorganization. Reorganization increases the performance-rate even in the hedging environment. It is of note that with hedging, egalitarian outperforms the others. Agents employing performance and inventory reorganizations diminish their maximum value at the time points of 2800 and 3500, due to the number of *isolated agents* (agents without neighbors/connections).

Figure 5 depicts the number of isolated agents in each agent simulation due to reorganization.

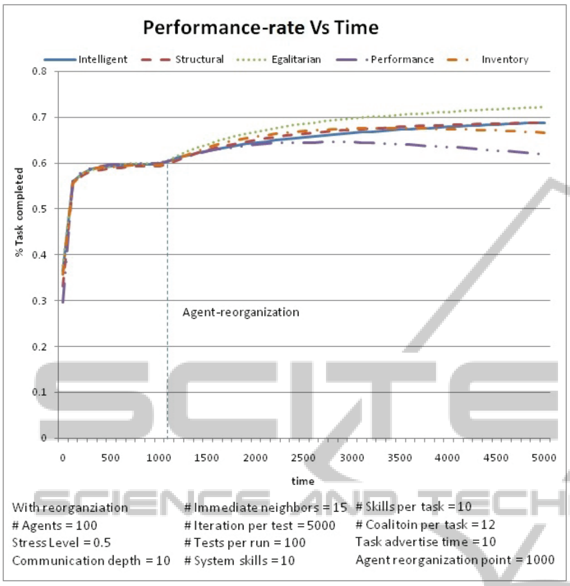

Figure 4: Performance-rate Vs Time (with reorganization).

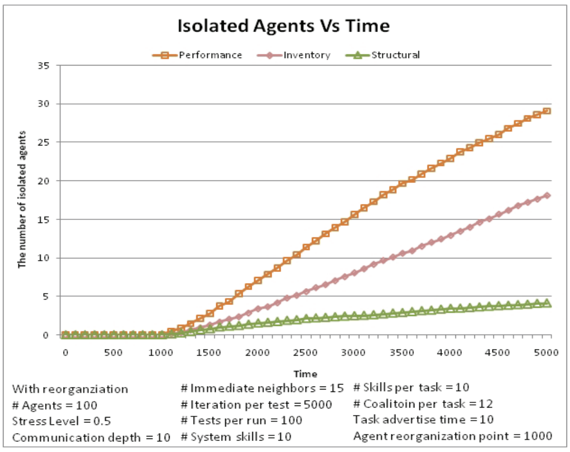

Figure 5: Isolated Agents Vs Time (with reorganization).

8 CONCLUSIONS

Our research shows that strategic agents are significantly better than random agents and, for a high number of connections, are competitive with the upper bound (hedging environment).

Success of local strategies (without hedging) depends heavily on having sufficient neighbors. The results show us that hedging agents are capable of earning more profit than others as their increased success negates the extra cost of discarding unnecessary coalitions, and strategic agents are competitive with them.

Agents employing egalitarian reorganization outperform all other reorganizations. Performance and inventory reorganization result in a high number of isolated agents.

A better plan would be to have a mixture of strategies: some which directly pursue goals and others which seek to rebuild and utilize agents which have been abandoned in the simulation.

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