SIMULATING EMERGENT LEARNING BEHAVIOR FOR COMPUTATIONAL ORGANIZATIONS

Pi-Sheng Deng[a]
Eleftherios G. Tsacle[b]

[a,b]Department of Computer Information Systems,
College of Business Administration,
California State University, Stanislaus, USA
[a] deng@toto.csustan.edu
[b] tsacle@toto.csustan.edu

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Abstract

In this research, we conceptualize organizational learning as a manifestation of the collective learning behavior of knowledge agents in an organization. In a coalition or community of practice, each member possesses partial but complementary knowledge, so that only the team working together as a whole has the full body of knowledge. Organizational learning is exhibited as the change of organizational processes for accomplishing tasks through the collaborative work of members of a coalition.

Keywords: Computational organizational learning, Collaboration, Coalition, Community of Practice, Knowledge market, Single-loop learning, Double-loop learning.

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Suggested track: G Organizational learning

1 INTRODUCTION

Today’s business is becoming more complex, dynamic, and globally competitive. To excel in such a changing and highly dynamic business environment, organizations must be able to improve continuously (Winter, 1994). Garvin (1994) of Harvard University states that "Continuous improvement requires a commitment to learning." In a learning organization, people continually expand their capacity to achieve their shared vision through learning how to work collaboratively with each other (Senge, 1990).

In this research, we conceptualize organizational learning as a manifestation of the collective learning behavior of knowledge agents in an organization. An organization learns as its members interact dynamically with each other or with the organization’s external environment, and experiences resulting from this dynamic interaction lead to more successful performance. In an organization, employees are the major source of knowledge, and these knowledge agents interact with each other for acquiring knowledge, via sharing or exchange, in accomplishing organizational goals or objectives. The interaction among knowledge agents can be likened to a knowledge market in which various kinds of knowledge transactions take place. Through knowledge transactions, there will be a re-distribution of knowledge “wealth” in an organization.

Though traditional research on organizational learning assumes individual mastery and acquisition of the knowledge needed for accomplishing the task, many studies indicate that knowledge in organizations is often tacitly shared by members of communities of practice, and exists in the distinct practices and relationships that emerge from the coordinated accomplishment of tasks over time (Badaracco, 1991). Similarly, March (1981) proposes his model of decision making in organizations, for which he sets aside the assumption of a single or unified decision maker, developing instead the concept of a loose and shifting “coalition” that selects or accomplishes organizational goals. In a coalition or community of practice, each member possesses partial but complementary knowledge, so that only the team working together as a whole has the full body of knowledge (Badaracco, 1991; Tsoukas 1996). The tacit knowledge can be possessed by members of a team or an organization to the effect that they know which agents in the organization have the expertise in certain areas (Winter 1987). Organizational learning is exhibited as the change of organizational processes for accomplishing tasks through the collaborative work of members of a coalition (March & Olsen, 1976). It has been shown that collaborative learning usually results in a higher efficiency compared to individual learning (Liu & Yao, 1998).

The above thoughts have been incorporated into the design of our market-based conceptual model for collaborative learning (Deng & Tsacle, 2003). In our conceptual model, an organizational task is accomplished through the cooperation of a group of experts participating in a coalition (or a community of practice) and working on the task in a sequential manner. Membership of the coalition is subject to change, through the market mechanism, according to the contribution each member made toward the task accomplishment, and this membership modification over time can be regarded as the change of organizational processes. Therefore, we can theorize that an organization learns through the modification of membership for the community of practice or coalition in achieving organizational goals over time.

In this research cooperative learning occurs as an emergent phenomenon of adjustment of agent wealth. Each agent’s wealth is affected by transactional activities in the knowledge market. In our model, there are three mechanisms related to wealth adjustment which is induced by knowledge transactions. These three mechanisms contain parameters which are used to specify how to pay the knowledge-providing agents, how to select agents for participating in the collaborative learning process, and how to reward those agents participating in contributing to a joint success. Different parameter values have different effects on collaborative learning. We conduct simulation to systematically analyze the effects of different parameter settings on the consequences of each mechanism, and the effects on the emergence of double-loop learning which also leads to organizational innovation and continuous improvement.

Through our simulated computational knowledge market, we attempt to facilitate the understanding on the mechanisms that enable organizational learning as an emergent phenomenon of interaction, either competition or collaboration, among knowledge agents of an organization. The simulation result allows us to investigate how re-distribution of knowledge wealth of agents affects organizational learning through knowledge transactions in the organizational knowledge market.

2 A Market-Based Computational Model for Organizational Learning

An organization is a knowledge market where buyers, sellers and brokers of knowledge participate collaboratively in knowledge transactions for accomplishing organizational tasks (Davenport and Prusak, 1998). In each knowledge transaction, buyer agents interact directly, or via knowledge brokers, with seller agents in obtaining or exchanging the needed knowledge for improving the organizational performance. According to Simon (1983), learning results in adaptive changes in a system that enables the system to do the same task or similar tasks more effectively the next time.

Deng & Tsacle (2003) proposed a computational learning model for artificial organizations. An artificial organization is regarded as a knowledge market, and consists of knowledge agents collaborating in accomplishing tasks. In this artificial organization, the broker agent identifies a group of agents for the organizational tasks. This group of agents will compete for the privilege of providing their expertise or services to buyer agents. A major assumption of that model is that none of the agents has enough knowledge to complete the task alone. Individual agents possess partial but complementary knowledge, and agents must collaborate for task completion.

In such a collaborative learning environment, the completion of a task needs a chained series of consultation with expert agents. The complexity of the task might entail the winner agent to seek help or advice from the other agents in complementing its own insufficient knowledge for the task. Through a sequence of such “outsourcing” processes in identifying qualified expert agents whose expertise can complement the buyer agents’ insufficient knowledge, a team or coalition of agents will emerge to accomplish the task. In other words, a complex social system is constructed through collaboration in the organization (Weick and Roberts, 1993).

During the coalition formation process, knowledge agents are selected for participation based on their strength, representing their potential ability for problem solving, and their capital, representing their accumulated contributions in the organization. Deng & Tsacle’s model is for multiple-step learning tasks. Tasks will be completed through the collaboration among experts in the sense that they form a chain of “upstream-downstream” working relationship with each agent contributing to part of the task completion. Through the transactions in the knowledge market, an agent’s capital and strength will be modified stochastically, and the organization will develop more efficient chains of agents for accomplishing the tasks over time.

Deng & Tsacle’s model is driven by three major processes: the Expert Selection Process, the Plan Formation Process, and the Capital Reallocation Process. The Expert Selection Process selects a winner agent from the group of agents as identified by the broker agent. Due to the assumption of this model that none of the agents has the complete knowledge for task completion, a series iterative processes of task decomposition and winner selection will be initiated by the Plan Formation Process. During the plan formation process, buyer agents will pay the seller agents for their services. The final plan is subject to organizational evaluation in terms of how effective it is in achieving the tasks, and participants of this plan will be rewarded for their contributions. The rewarding functions are performed by the Capital Reallocation Process, and will result in the adjustment of agent capitals.

The adjustment of agent capitals via the Capital Reallocation Process will enable the organization to learn at both the local level, in the sense that better agents will be chosen from each local competition next time when the same task is performed, and at the global level, in the sense that a better plan for the task will emerge through the improved performance at the local level. Since a plan can be regarded as a strategy for tackling an organizational task, generation of a new plan (or strategy) at the global level through a sequence of nested performance improvement at the local level can be regarded as “pseudo” double-loop learning in the organization.

This model is characterized by the expert agents (or seller agents) competing with each other locally to become a winner, while buyer agents collaborate with each other globally in forming a plan for task accomplishment. The model is shown in Fig. 1.

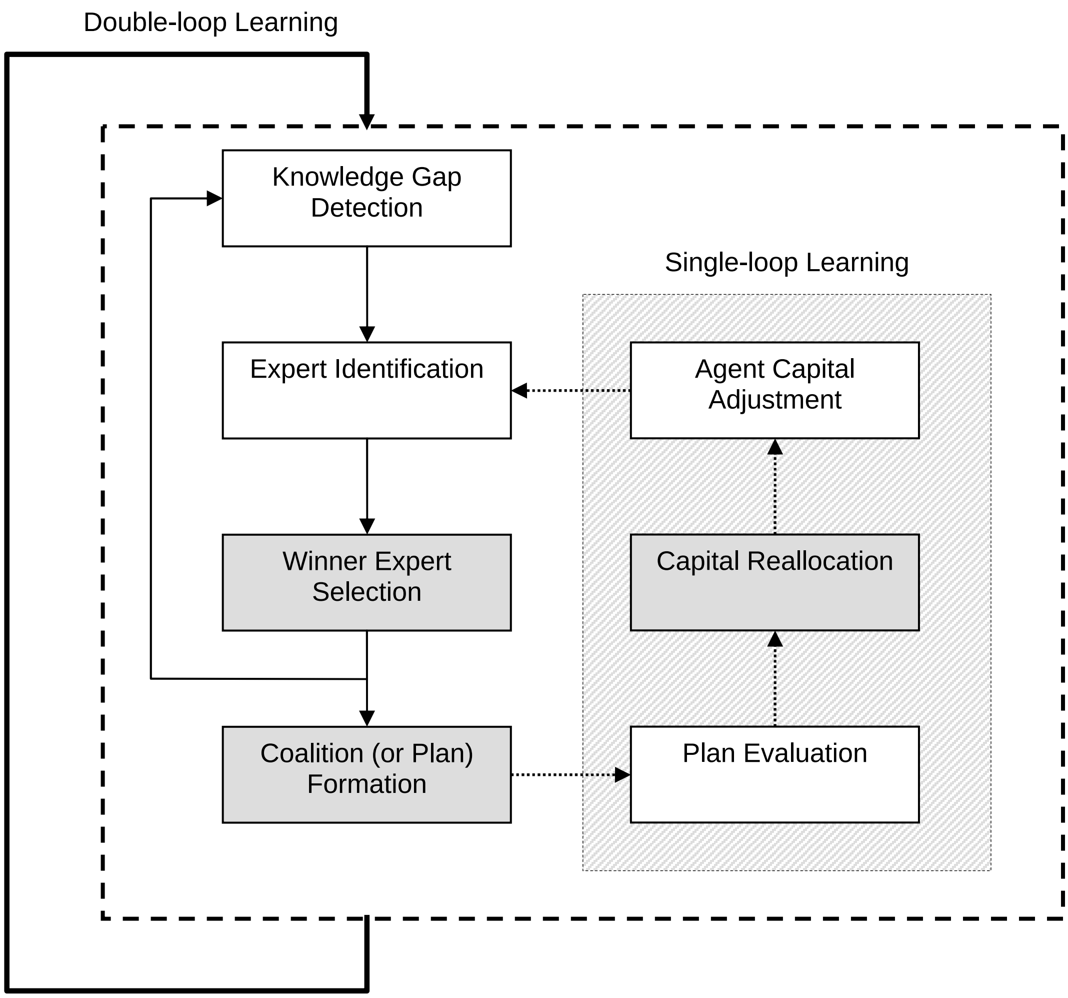

Fig. 1. A computational model for organizational learning.

Expert Selection Process: We summarize the Expert Selection Process in the following algorithmic steps:

Step 1. A knowledge gap for the original task assigned to the agent who becomes the first buyer agent is identified.

Step 2. A knowledge broker initiates the process of bridging the gap by identifying an initial set, **KB**, of candidate expert agents, which are motivated by market incentives, competing to become an outsource provider for the subtask.

Step 3. Each expert agent, K, has strength, s_K, which is defined as a function of attributes representing the length of the ability vector as: $(\sum_{i=1}^{n} a_{K,i}^2)^{1/2}$. Buyer agent has a preference distribution over the set of attributes being selection criteria. Based on the set of n selection criteria, the model generates n subsets of candidate expert agents, $\mathbf{KB}_i$, i = 1, 2, … , n.

Step 4. For each candidate agent, K, in each subset, we calculate the agent's relative importance index as:

$$I_{K,\,\mathbf{KB}_i} = \frac{s_K\,\chi_{\mathbf{KB}_i}(K)}{\sum_{k\in\mathbf{KB}} s_k\,\chi_{\mathbf{KB}_i}(k)}, \text{ for each } K \in \mathbf{KB}, \text{ where}$$

$$\chi_{\mathbf{KB}_i}(x) = \begin{cases} 1, & \text{if } x \in \mathbf{KB}_i \\ 0, & \text{otherwise} \end{cases}$$

Step 5. For each agent K, calculate its weighted importance index and the overall weighted importance index from n subsets of experts.

$$\mathbf{wI}_K = \sum_{i=1}^{n} w_i I_{K,\,\mathbf{KB}_i}, \text{ for each } K \in \mathbf{KB}, \text{ where}$$

$$w_i = \frac{\sum_{k=1}^{|\mathbf{KB}|} a_{k,i}}{\sum_{k=1}^{|\mathbf{KB}|}\sum_{j=1}^{n} a_{k,j}}, \; i = 1,\ 2,\ \ldots,\ n.$$

Step 6. Compute the deviation of each agent K's overall weighted importance index from the group average.

Compute the deviation of each agent K's capital, C_K, from the group average.

Apply a sigmoidal function to the sum of the above two deviations to generate selection probability distribution, $[p(K_1), p(K_2), \ldots, p(K_{|\mathbf{KB}|})]$, for the entire group of candidates.

$$p(K) = \frac{1}{1+\exp\left(-\lambda\left(\left(\mathbf{wI}_K - \frac{\sum_{k\in\mathbf{KB}} \mathbf{wI}_k}{|\mathbf{KB}|}\right) + \left(C_K - \frac{\sum_{k\in\mathbf{KB}} C_k}{|\mathbf{KB}|}\right)\right)\right)}, \text{ for each } K \in \mathbf{KB}.$$

In the above formula, the parameter λ determines the steepness of the sigmoidal function, and is mainly for moderating the influence of accumulated capital on the selection probability. For this purpose we design the values for λ as 0 < λ < 1. The parameter λ affects the probability of agents with different amount of accumulated capital and different strengths of abilities to be chosen as the winner agent in the local selection competition process.

Step 7. Randomly select the winner agent based on the set of probability distribution.

Plan Formation Process: The Plan Formation Process can be summarized in the following steps: (Continued from the previous step number.)

Step 10. Add the winner agent to the set of collaborative agents.

Step 11. If the winner agent has a knowledge gap, repeat Steps 1 through 7. In this case the winner agent now becomes a buyer agent.

Step 12. If the winner agent does not have a knowledge gap, the collaborative set of agents is complete, and is regarded as forming a plan for accomplishing the original task.

Capital Reallocation Process: The Capital Reallocation Process consists of two activities of capital transfer at both the local and the global levels. The local capital transfer takes place after Step 7 when the winner agent is selected, while the global capital transfer takes place after the coalition is formed (Step 12) for task completion. This capital reallocation mechanism can be summarized in the following four steps:

<u>Local Capital Transfer</u>

Step 8. Calculate the capital-adjustment parameter, c, for computing payoffs at the local level.

$$c = \frac{s_{winner}}{\sum_{k \in \mathbf{KB}} s_k}.$$

Step 9. The winner agent and the broker agent receive payoffs from the buyer agent, while the buyer agent's capital is reduced accordingly.

<u>Global Capital Transfer</u>

Step 13. Global transfer of capital. Rewards by the organization are assessed to the coalition of winner agents commensurate to their "effective" contributions to the completion of the original task.

Step 14. Update the strength of each in the coalition.

$$s_{K,\text{after}} = (1 + rate_K) * s_{K,\text{before}} - \frac{rate_K * s_{K,\text{before}}^2}{s_{coalition}},$$

where $rate_K$ is the learning rate of agent K.

Step 15. Update the abilities of each agent involved in the coalition.

$$a_{K,i,\text{after}} = \frac{a_{K,i,\text{before}}}{s_{K,\text{before}}} \times s_{K,\text{after}}.$$

3 Model Implementation

We built a prototype system for the implementation of our model. At first, we randomly generated a population of agents. This population represented the entire organization's employees. A set of attributes was defined by end users for agents in the generated population, and each attribute was defined on its respective domain. Then, we initialize the attribute values and capital for each agent by using a random number generator. Strength of each agent was then computed based on the attribute values. We applied the same set of attributes to define the skill requirements for the organizational task, with values randomly generated from the domain of each attribute. The task was randomly assigned to an agent in the entire population.

The knowledge broker in our prototype system was implemented as a pattern recognizer which compared each agent's attribute values with the organizational task's skill requirements. Only those agents whose attribute values greater than or equal to each corresponding task skill requirement were selected to form the **KB** set.

Based on this **KB** set, agents with values on attribute *i* greater than that of the task's attribute *i* were grouped into sub-groups $\mathbf{KB}_i$. Some agents would be included in multiple $\mathbf{KB}_i$'s. Due to the consideration that each attribute was defined on a different domain, values of attributes were first normalized to the same scale so that weight could be computed for each attribute. The weighted importance index of each agent was then computed. A sigmoidal function of weighted importance index and capital was applied to compute the probability distribution for agents involved in the **KB** set, and this probability distribution would determine the selection probability for each agent.

The winner agent received payment from the buyer agent in the form of capital increase. In order to determine if the winner agent alone could accomplish the subtask, we designed an intuitive algorithm in comparing the abilities of the winner agent and the first three most important skill requirements of the task. If the winner agent fell short of the threshold value on any of the three most important skill requirements, then the subtask would be sub-contracted out to another agent again, i.e., another local competition cycle would be activated. Through these, a coalition for the task would be eventually formed. Each agent involved in the coalition would be rewarded for its contribution to the completion of the organizational task. This whole process was counted as on simulation run of the learning cycle. We performed a sequence of simulation runs, and observed if our computational organization exhibited the phenomenon of double-loop learning.

For our simulation, we designed three tasks corresponding to three different levels of difficulty: Simple, Medium, and Difficult. The simple task requires only 5 attributes; the medium one requires 10 attributes; and the difficult one requires 15 attributes. We also set the sigmoidal function parameter (λ) at three levels: 0.01, 0.2 and 0.8, representing slow, medium, and fast slope of the sigmoidal function respectively. We conducted each simulation until the size of the coalition was no more than ±1 of a certain number for at least 5 learning cycles. Our simulation results were presented in Fig. 2~Fig. 7.

Performance vs. Sigmoidal Function Parameter (λ)

Fig. 2~ Fig. 4 show the patterns of convergence of coalition size over time, .i.e., the organizational learning performance in performing the same task over time. From Fig. 2 and Fig. 3, they show that for simple and medium tasks, the steep slope of the

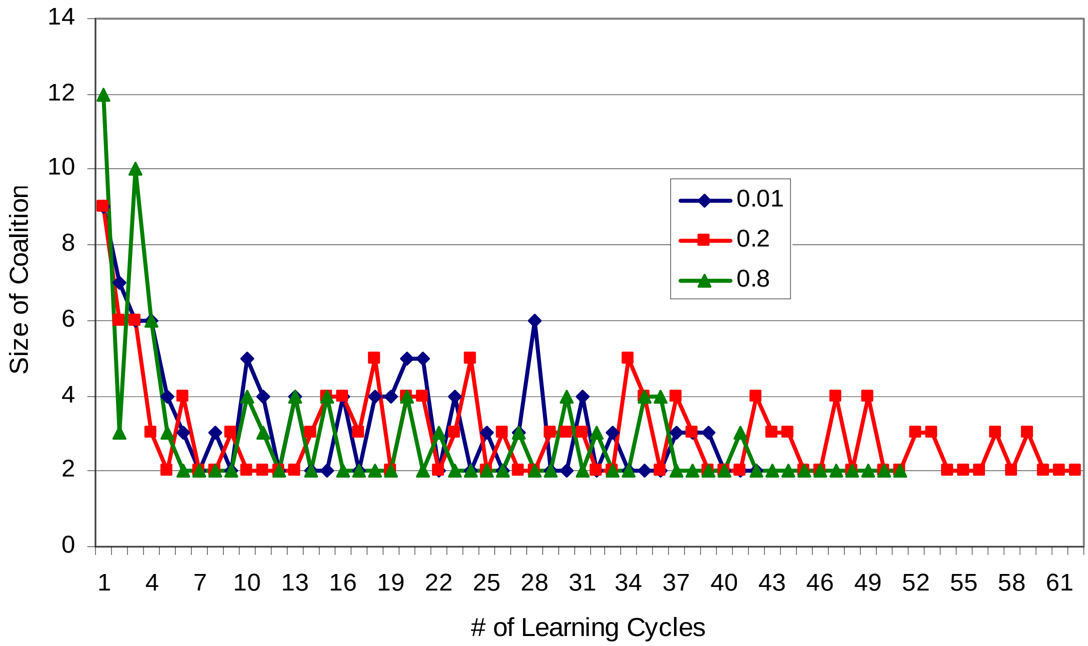

Fig. 2. Learning performance for simple tasks.

sigmoidal function (means choosing the rich or capable agents more frequently) will converge more steadily, while the moderate slope will cause more fluctuation for the collation size, and will take longer to converge to the final coalition size.

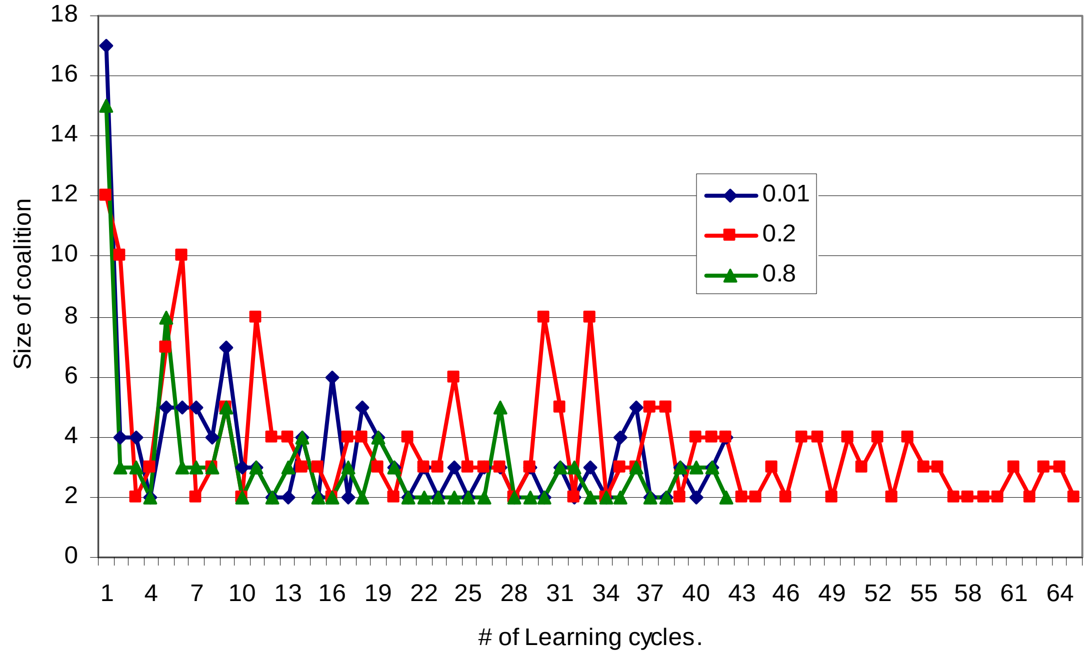

Fig. 3. Learning performance for medium tasks.

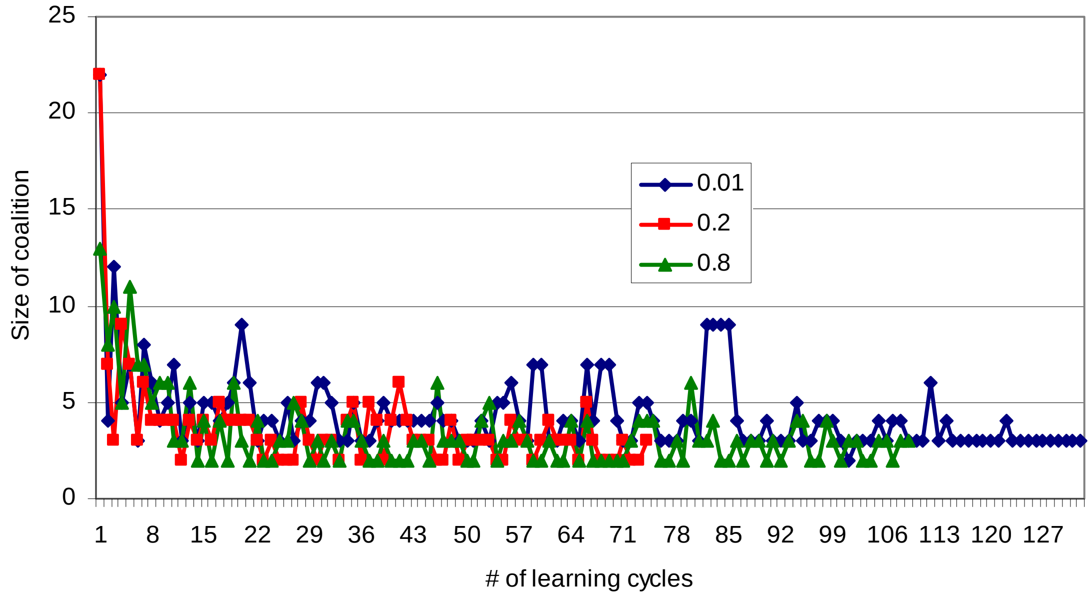

Fig. 4. Learning performance for difficult tasks.

However, from Fig. 4, it is interesting to observe that for difficult tasks, the medium slope (means choosing the rich or capable agents with moderately probabilities, and giving not rich or not so capable agents some probabilities to be chosen) will cause less fluctuation for the coalition size, and will converge more steadily to the final coalition size. From Fig. 4, it seems that the slow slope (means not differentiating between rich/capable and not-rich/not-capable agents very much) will be least desirable for task performance, and it converges to a coalition size larger than the other two learning rates.

Performance vs. Complexity of Tasks

From Fig. 5, it shows that slow slope (means not differentiating between experienced and inexperienced agents or capable and incapable agents) will require more learning cycles to converge to the final coalition size when performing difficult tasks. Fig. 5 also indicates that organizations will learn faster for tasks with medium level of difficulty when the sigmoidal function slope is slow.

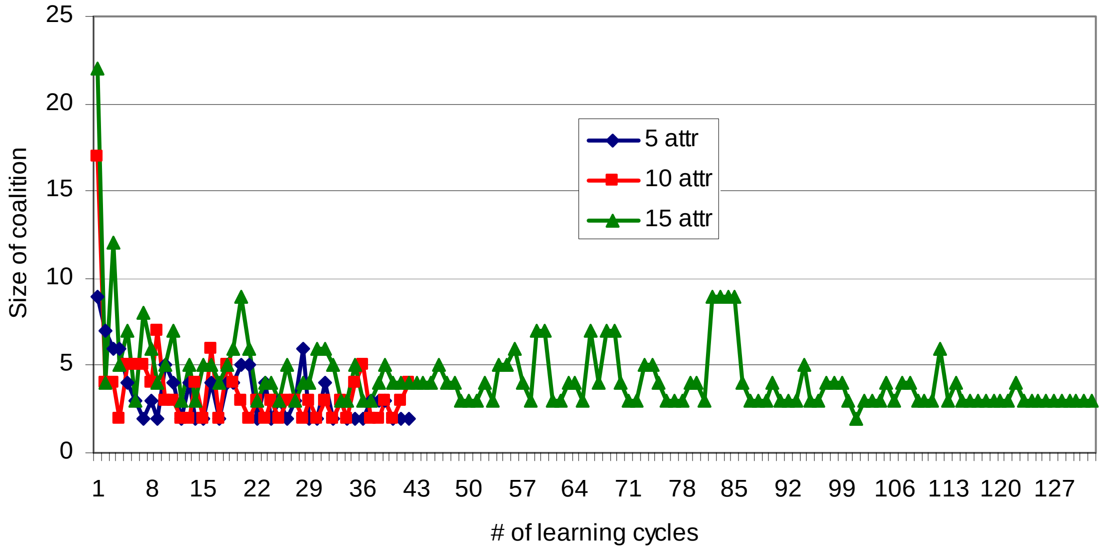

Fig. 5. Learning performance for the parameter $\lambda = 0.01$.

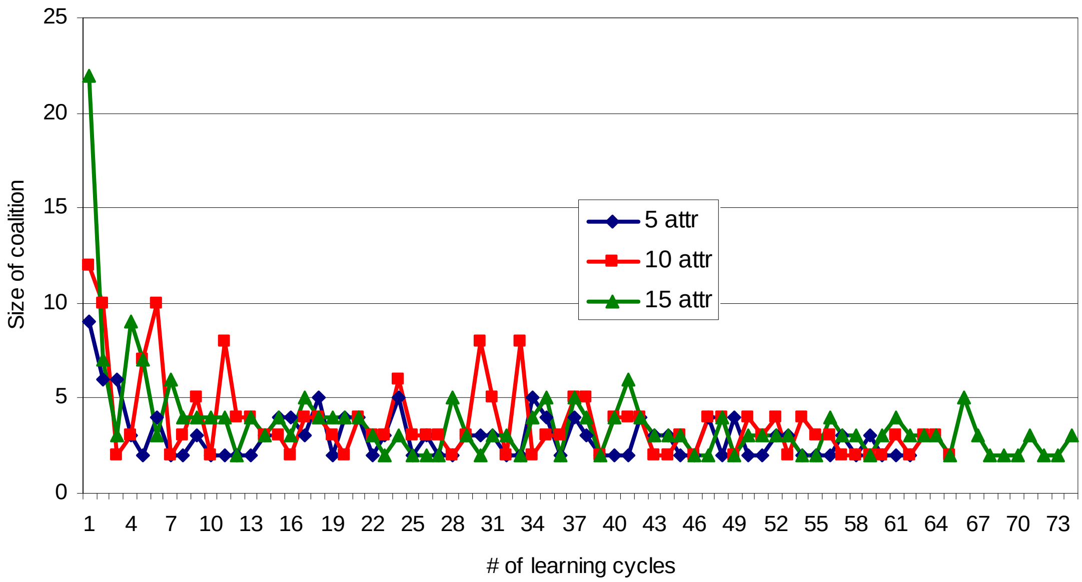

Fig. 6. Learning performance for the parameter $\lambda = 0.2$.

From Fig. 6, it shows that with medium level of slope (means giving inexperienced or in capable agents some opportunities to become winners), organizations will perform best for simple tasks. Though the coalition-size fluctuation is larger for medium-sized tasks, it takes less learning cycles for medium-sized tasks to converge to the final coalition than large-sized tasks.

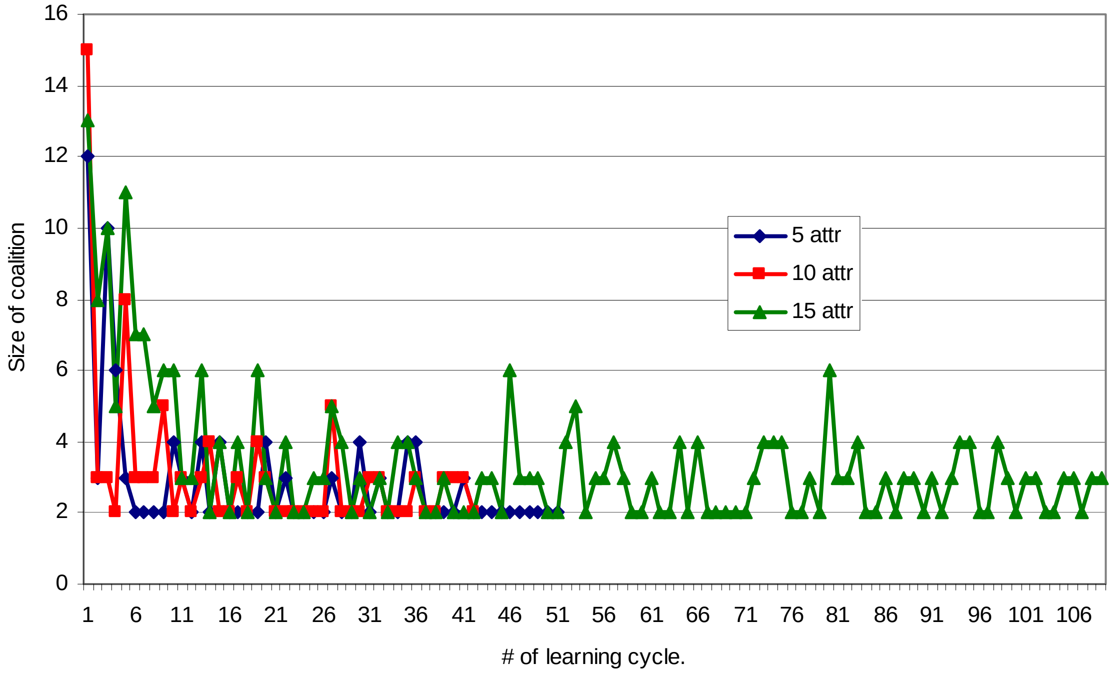

Fig. 7. Learning performance for the parameter $\lambda = 0.8$.

As to steep slopes (means choosing experienced or capable agents only), the results are different as shown in Fig. 7. For difficult tasks, organizations will take a long period time to converge to a final size of coalition. When the slope is steep, organizations seem to perform best for taks with medium level of difficulty.

4 Discussion & Conclusion

In this paper, we implemented a market-based organizational learning model. Based on this model, coalitions of agents would emerge with upstream downstream relationships among the agents. We conducted simulations for tasks representing three different levels of difficulty with three different strategies for selecting agents as reflected through the slopes of the sigmoidal function which generates selection probabilities for agents. The simulation results showed that the model allowed the organization to exhibit learning behavior through improved performance in performing the same task over time. The performance of the organization in performing the task was measured in terms of the number of agents involved in the formation of coalitions in completing the task.

In this paper, we have experimentally demonstrated organizational learning as a consequence of a multi-stage optimization process through capital re-allocation. Our work also complemented the current research which presumes individual mastery of explicit and codified knowledge for single-step tasks through the formation of coalitions (or communities of practice) in accomplishing organizational tasks. Our implementation showed that there was single-loop learning occurring at the local competition level, i.e., a winning agent had higher chance of being selected as the winning agent again when the task was performed again. Also, there was double-loop learning occurring at the global level, in which the number of agents involved in coalitions would gradually decrease when the same task was performed repeatedly.

For future research, we will continue to investigate how different pricing scheme and different rewarding scheme would affect the formation of coalition. We will also design different algorithms for the broker agent and investigate how it would affect organizational learning. Finally, our current version of deciding task decomposition is on the rule of thumb basis, and better criteria should be devised for this decomposition decision.

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