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A SELF-ORGANIZATION MODEL FOR AUTONOMOUS AGENTS IN A DECENTRALIZED ENVIRONMENT[1]

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Abstract. A self-organization model for autonomous agents operating in a transparent decentralized environment is developed and investigated. Transparency means that all information about the environment and the agents' community is open. Each agent informs the entire community about his current resources and intentions. The environment consists of cells, and during operation, each cell can generate a new resource using the resources received from agents. Each agent is also aware of the efficiency and resources of the cells. The agent-based approach is adopted to consider the efficient allocation of agents' resources in cells and analyze different resource allocations. Each agent acts rationally based on his goals. An iterative resource allocation method is proposed, in which the agents exchange information to make their decisions. Computer simulations are carried out for several modes of operation: 1) without learning but with iterations, 2) with learning and iterations, 3) without learning and iterations, and 4) with learning but without iterations. As indicated by the simulation results, the total resource of the agents' community is significantly higher in the model with learning and iterations; due to self-organization and learning, the agents are distributed so that their number in each cell is small. According to the experimental evidence, learning works only in combination with iterations.

Keywords: multi-agent systems, self-organization, decentralization, transparent environment.

INTRODUCTION

In research into artificial intelligence, the theory of *multi-agent systems* has become widespread in recent decades. The multi-agent approach is used in optimization and control, collective behavior and market modeling, and investment allocation. Unlike dynamic systems, discrete-event modeling, and system dynamics, the individual characteristics of agents and their local interaction are important in this approach: the model can be constructed bottom-to-top. Therefore, it is possible to observe how the interaction of agents affects the overall behavior of the entire system. Currently, there exist many models and lines of research in this area [1–4]. One line is *self-organizing* multi-agent systems [5, 6]. The importance of *self-organization* was emphasized by W. Ashby [7]. Multi-agent systems allow studying self-organization processes and describing complex systems and have high flexibility. Also, note some papers on multi-agent systems and related ones on robot communities [8, 9].

The theory of multi-agent systems often operates two closely related concepts: distributed artificial intelligence (DAI) and decentralized artificial intelligence (DzAI). Let us explain their difference. Speaking about the problems solved within these approaches, we indicate that DAI is intended for the joint global control of a distributed group of agents. The solution of such problems is joint because mutual information exchange helps perform one common task. Unlike DAI, DzAI focuses on the activities of an autonomous agent in a multi-agent world. This approach employs the concept of "agent" widely, referring to a subject who acts rationally based on his goals. Moreover, an autonomous agent may exist regardless of other autonomous agents. Autonomous agents can cooperate and exchange information in a common world for performing personal or global tasks. Thus,

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in DAI, a certain global task is initially defined, and it is required to design distributed objects to perform it. In DzAI, decentralized autonomous subjects are first defined, and the main problem is to study their behavior to understand what tasks they can perform [10]. In this paper, we will follow the decentralized approach.

The phenomena of "competition" and "cooperation" are of particular interest in multi-agent modeling. In the paper [11], R. Axelrod experimentally proved the profitability of cooperation for two competing players based on game theory and computer simulation. He constructed and studied a multi-agent model consisting of a community of competing agents in which each agent has independent decision-making. Due to cooperation (information exchange and transparent environment) and learning, more efficient operation of the entire system is possible.

This paper develops the authors' previous research into collective behavior processes in a transparent environment [12–14]. Note that "transparent environment" is not a strict term accepted in the scientific community. However, in recent years, it has been frequently encountered in socio-economic studies. We will assign it an interpretation close to the term "transparent market" in economics [15]. This paper aims at showing that in the course of competition and cooperation, autonomous agents can be distributed in cells—singly or in small groups—using learning and iterative information exchange about the environment's state.

1. MODEL DESCRIPTION

Let us give a formal description of the model. Consider some environment consisting of numbered cells. The number of cells is fixed and equal to M. Each cell is characterized by its efficiency k_i and resource R_{i0}, which does not change over time. Assume that during operation, each cell can generate a new resource using the available resource. In this paper, the resource is similar to the capital of investors and producers and the cells to producers [12–14]. Unlike the models from [12–14], the cell's resource does not change. The parameter k_i characterizes how efficiently cell i can process the available resource.

A community of N agents operates in the environment. Each agent j is also characterized by his resource K_j. The agent allocates a share of his resource to some cell, receiving back a share of the generated resource. Moreover, agent j receives a share of the generated resource from cell i proportionally to his contribution to this cell. Agents operate during T periods in the transparent environment in the same way as described in [12–14]: they have complete information about the efficiency of cells and the total resource of each cell after receiving resources from other agents.

Note that time is divided into periods, and each period has a sufficient number of iterations. The periods are numbered by $T = 1, 2, \ldots, N_T$ and the iterations by $t = 1,2, \ldots, t_{\max}$. One period T includes several stages:

– stage 1, representing an iterative process in which the agents decide on a resource allocated by a particular agent to a certain cell,

– stage 2, allocating agents' resources to cells,

– stage 3, receiving newly generated resources from the cells,

– stage 4, agents' learning.

At the beginning of period T, agents choose shares of their resources to be allocated to particular cells. This decision is made during an *iterative process* (step 1), considered in detail below. Each agent can select any number of cells for resource allocation.

Let us first describe stages 2 and 3 in period T. Assume that after receiving the resources from all agents (stage 1), cell i has the total resource

$$R_i = R_{i0} + \sum_{j=1}^{N} r_{ij}\,, \tag{1}$$

where r_{ij} is the resource allocated by agent j to cell i. The resource that all agents in aggregate can receive from cell i is equal to

$$E_i(R_i) = \exp(-k_s s_i) k_i \varphi_i(R_i)\,, \tag{2}$$

where k_i denotes the efficiency of cell i ($0 < k_i \le 1$); k_s is the resource spent by the cell on one agent (for example, the resource consumed for interacting with the agent); s_i is the number of agents selecting cell i; φ_i stands for a cell performance function given by

$$\varphi_i(x) = \alpha_1\left[1 - \exp(-\alpha_2 x)\right], \tag{3}$$

where α_1 ($\alpha_1 \in \mathbf{R}$) and α_2 ($0 < \alpha_2 \le 1$) are some parameters. Figure 1 shows the graph of the performance function (3). In contrast to the paper [13], the performance function is nonlinear and more flexible for adjustment. Note also that formula (2) for calculating the new resource generated by the cell differs from the one considered previously [12–14] by the factor $\exp(-k_s s_i)$. This factor in (2) reduces the generated resource: the more agents interact with the cell, the greater the decrease will be. In the papers [12–14], such consumption was not taken into account for producers. As shown by computer simulations below, the agents with this consumption can be learned and distributed in cells in small groups.

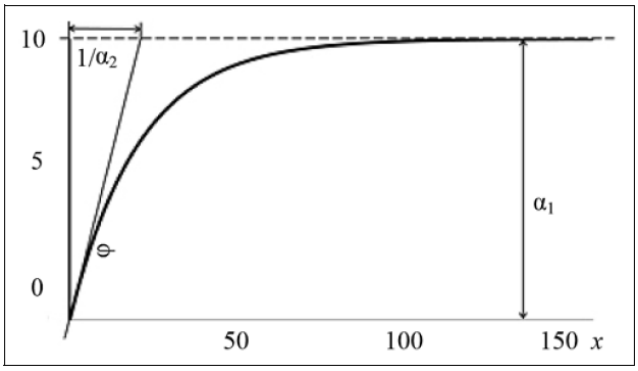


Fig. 1. Graph of performance function with $\alpha_1 = 10$ and $\alpha_2 = 0.05$.

At stage 3 of period *T*, the resource received by each agent from cell *i* is calculated by the formula

$$P_{ij} = E_i(R_i)\frac{r_{ij}}{\sum_{l=1}^{N} r_{il}},$$

Since the environment is transparent, each agent has information about the efficiencies of all cells and the intentions of all other agents.

The total resource received by agent *j* in period *T* is the sum

$$SP_j = \sum_{i=1}^{M} P_{ij}.$$

Next, the resource of agent *j* is increased by the value SP_j:

$$K_j(T) = K_j(T-1) + SP_j.$$

The total resource of the entire community at the end of period *T* is the sum

$$SK(T) = \sum_{j=1}^{N} K_j(T).$$

The agents choose the shares of the resources to be allocated to a particular cell during the following iterative process (stage 1). At the first iteration, the agents consider the efficiencies of all cells and the resource of a given cell for estimating the effect obtained from it. The estimates are calculated by the formula

$$A_{ij} = d_{ij} k_i \varphi_i(R_{i0}), \qquad (4)$$

where d_{ij} specifies the current degree of belief of agent *j* to cell *i*. At the beginning of operation, the degrees of belief are all equal to 0.1. During the iterative process, the degrees of belief remain the same: they will change with learning at stage 4 of period *T* (see the description below).

At the second and subsequent iterations, the intentions of other agents are considered, and the estimates are calculated by the formula

$$A_{ij} = d_{ij} P_{ij} = d_{ij} \exp(-k_s s_i) k_i \varphi(R_i') \frac{r_{ij}}{\sum_{l=1}^{N} r_{il}}, \qquad (5)$$

where R_i' is the expected resource of cell *i* after the contributions of all agents; r_{il} denotes the resource to be allocated by agent *l* to cell *i* (see the previous iteration). The resource R_i' is calculated by formula (1). Thus, the value R_i' is iteratively recalculated considering the intentions of all agents. The resource received by the cell is determined at the last iteration. In computer simulations, the model's behavior was studied for the modes with iterations and without iterations. In the latter mode, the estimates are once calculated by the agents using formula (4). (Formula (5) is not involved here.)

After receiving the estimates, the agents choose shares of their resources for allocating to each cell. The resource allocated by agent *j* to cell *i* is calculated by

$$r_{ij} = K_j \frac{A_{ij}}{\sum_{l=1}^{M} A_{lj}},$$

where K_j specifies the resource of agent *j*. A sufficient number of iterations are performed; at the last iteration, each agent chooses a share of his resource for allocating to a particular cell. This share is equal to the resource r_{ij} obtained at this iteration.

At the end of each period *T*, the agents are learned (stage 4). Learning takes place without a teacher by changing *the degrees of belief* to the cells. As soon as the agent knows the resource received from the cell (stage 3), he recalculates the current degrees of belief according to the rule

$$d_{ij}(T+1) = d_{ij}(T) + \beta Q(P_{ij})\left[1 - d_{ij}(T)\right] - \gamma d_{ij}(T),$$

where β ($0 < \beta \le 1$) is the learning rate; $Q(x) = x / (1 + x)$; P_{ij} represents the resource received by agent *j* from cell *i*; γ ($0 < \gamma < 1$) denotes the "forgetfulness" parameter. Thus, the values d_{ij} are reestimated depending on the resource received by the agent from a particular cell. The greater the resource received is, the higher the agent's belief to this cell will be. Note that if the profit increase is insignificant, the degree of belief will be reduced. The last term characterizes a decrease in the degree of belief due to skills "forgetting." In computer simulations, the modes with learning and without learning were compared. In the mode without learning, the degrees of belief remain the same between periods: each period has no stage 4.

This learning algorithm allows adjusting the degrees of belief so that the agents are distributed in different cells. Different distribution patterns were analyzed using computer simulations.

2. SIMULATION RESULTS

For the model under consideration, we developed a computer program and carried out numerical experiments. The following values of the basic parameters were used: the number of periods $N_T = 100$; the number of iterations in each period, $t_{\max} = 150$; the number of agents $N = 5$, 10, or 20; the number of cells $M = 10$ or 30; the performance function parameters $\alpha_1 = 10.0$ and $\alpha_2 = 0.05$; the learning rate $\beta = 1.0$; the "forgetfulness" parameter $\gamma = 0.8$; the resource spent by the agent in each cell, $k_s = 0.3$. The initial resources of all agents and the efficiencies of all cells were random and uniformly distributed on the range [0, 1]. Computer simulations were carried out for several operating modes of the model:

– mode 1 (without learning but with iterations),
– mode 2 (with learning and iterations),
– mode 3 (without learning and iterations),
– mode 4 (with learning but without iterations).

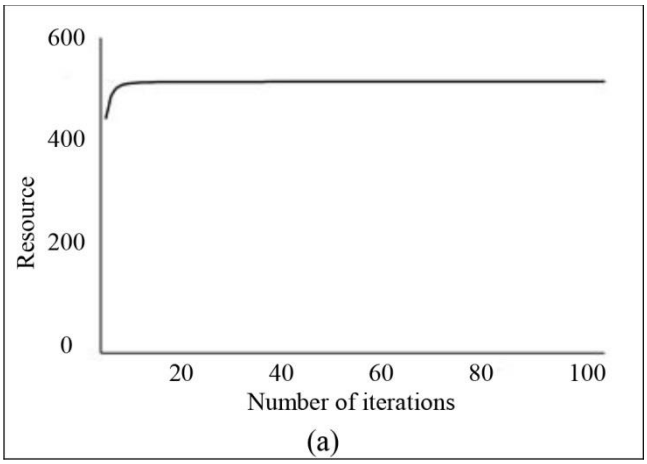
2.1. Convergence of iterative process

Figure 2*a*,*b* shows the final total resource of the agents' community depending on the number of iterations in the last period (modes 1 and 2). The data were averaged over one hundred different calculations. Clearly, the iterative process in mode 1 converges quickly. In mode 2, the iterative process is convergent as well.

Figure 3 presents the difference between the total resource obtained at iteration ($t + 1$) and during t iterations in mode 2. According to the simulation results, the total resource of the agents' community in this node is much higher than in mode 1; for details, see subsection 2.2. Due to this effect, the number of iterations $t_{\max}$ was set equal to 150.

2.2. Simulation results

Now we demonstrate that in mode 2, the agents' community accumulates a larger resource than in modes 1, 3, and 4. Figure 4 shows the total resource dynamics for the agents' community in these modes. Clearly, the total resource of the agents' community in mode 2 is much higher. At the same time, the total resource almost coincides in modes 3 and 4 (without iterations); in mode 1, the total resource slightly differs from that in modes 3 and 4. In modes 3 and 4 (without iterations), the agent's resource grows much slower than in those with iterations. Hence, we will analyze the modes with iterations only (modes 1 and 2), comparing them with one another.



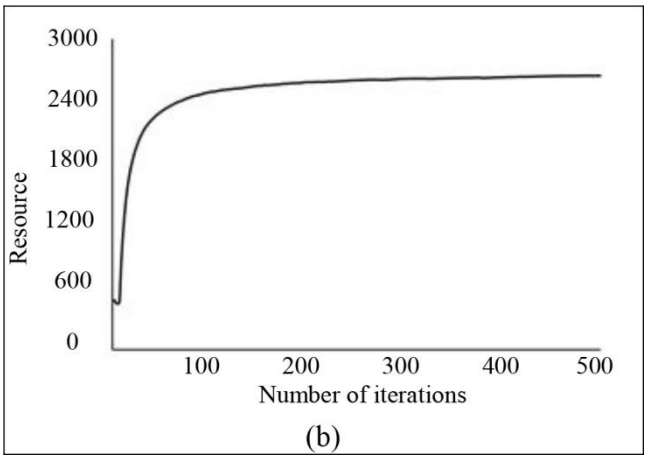


Fig. 2. Total resource of agents' community depending on the number of iterations ($N = 5$, $M = 10$, $T = 100$):
(a) mode 1 and (b) mode 2.

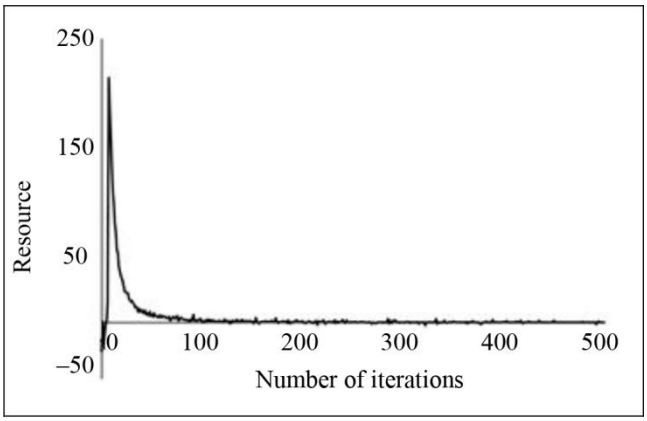


Fig. 3. Difference between the total resource obtained by agents' community at iteration ($t + 1$) and during t iterations in mode 2 with $T = 100$.

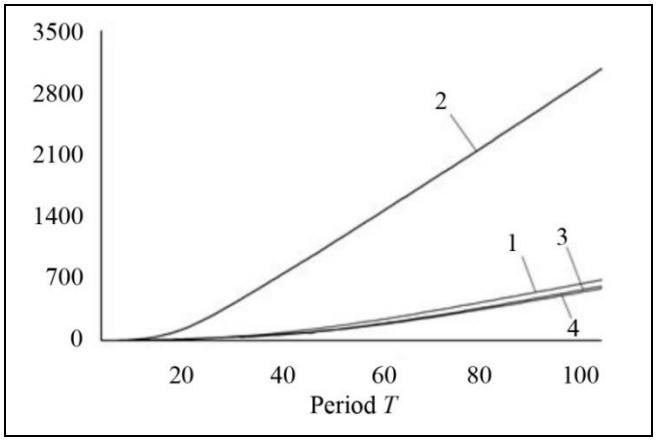


Fig. 4. The role of learning and iterations. Dynamics of community's total resource (N = 5, M = 10, t_{max} = 150) in different modes:
(*1*) without learning but with iterations, (*2*) with learning and iterations, (*3*) without learning and iterations, and (*4*) with learning but without iterations.

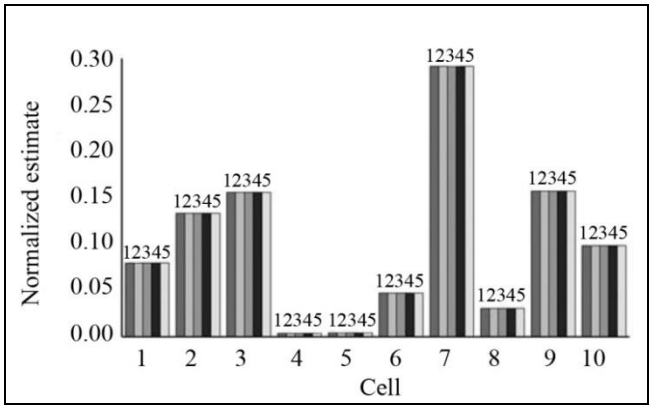


Fig. 5. Normalized estimates of cells at last iteration in mode 1:
t_{max} = 150 in period T = 2, N = 5, and M = 10. Agents are indicated on the diagram columns.

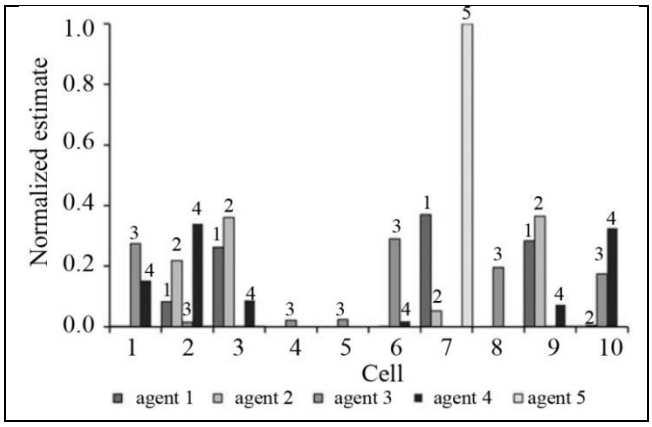


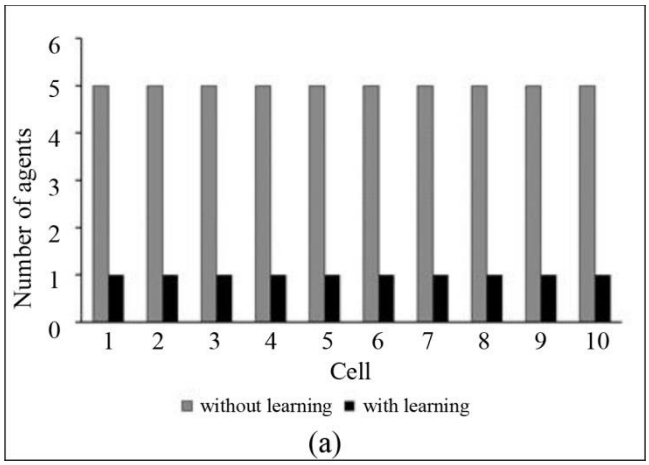
Fig. 6. Normalized estimates of cells at last iteration in mode 2:
t_{max} = 150 in period T = 2, N = 5, and M = 10. Agents are indicated on the diagram columns.

Thus, learning and iterations are effective only together. To explain this result, consider how agents rank cells in different modes according to formula (5). Let the most efficient cell be the one with the largest product k_iR_{i0}. First, we analyze the cell ranking procedure in mode 1 (without learning but with iterations). Figure 5 shows the normalized estimates calculated by the agents for each cell at the last iteration t_{max} = 150 of period T = 2. Clearly, the agents rank the cells in the same way: cell 7, most efficient, is followed by cells 3, 9, 2, 1, 6, 8, 5, and 4. Therefore, *cell ranking* is effective in mode 1. In this case, the agents do not compete with each other but *cooperate*: between iterations, the contribution to the more efficient cell increases synchronously for all agents.

Now let us include learning in the model and consider mode 2. Figure 6 shows the corresponding simulation results: the cell rankings according to formula (5) are different for different agents. When learning is included, the cell ranking procedure is supplemented by *the competition of agents*. The agents having a greater contribution to a given cell displace other agents from this cell gradually, changing the degree of belief between periods. For example, agent 5 allocates his entire resource to cell 7 (the most efficient one). Agents 1 and 2 also allocate some shares of their resources to this cell, but the picture will change over time (see Table 1): only agent 5 will stay in cell 7, whereas agent 1 will pass to cell 9, displacing the other agents from it.

Next, we examine the agents' distribution in cells in modes 1 and 2. First of all, note that each agent can select an arbitrary number of cells. In addition, if several agents select the same cell, then each agent receives less resource from the cell (see formula (2)). As it seems, the agents benefit from being distributed in cells singly or in small groups. Figure 7*a*,*b* shows how many agents select each cell in two modes with iterations – modes 1 (without learning) and 2 (with learning) – in the last period T = 100. The agents' distribution depends on their number and the number of cells as well.

We begin with the case when there are twice as many cells as agents (Fig. 7*a*). Clearly, during the operation of the entire community in the mode *with learning*, exactly one agent selects each cell. As emphasized above, one agent can allocate his resource to several cells. Despite this opportunity, in the mode with learning, the agents are singly distributed in cells. This effect is achieved through *iterations and learning*. Here we observe self-organization in the community of agents. In the mode *without learning*, each agent allocates his resource to all available cells according to the estimates A_{ij}. Clearly, each cell is selected by all ten agents. In this case, the resource allocated by an agent will depend on the cell's efficiency and resource.



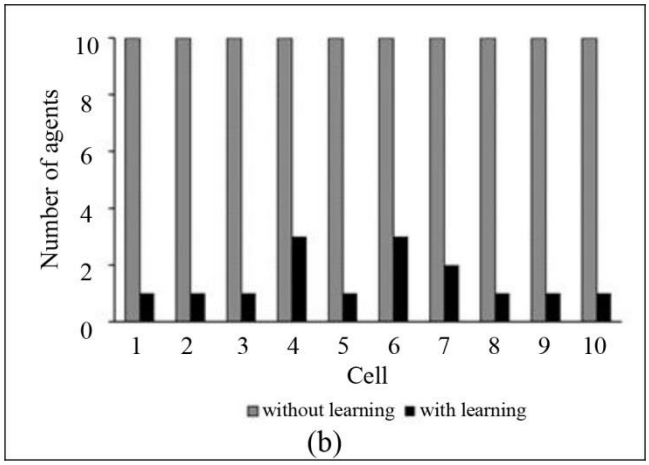


Fig. 7. Distribution of agents in cells:
(a) $N = 5$ agents and $M = 10$ cells, (b) $N = 10$ agents and $M = 10$ cells.

Now consider the case when the numbers of cells and agents coincide (Fig. 7*b*). In this case, the agents in the mode with learning are distributed in cells in small groups: one, two, or three agents per cell. In the mode without learning, the agents allocate their resources to the cells similarly to the previous case.

Increasing the number of agents and cells, we obtain results similar to Fig. 7; see Fig. 8. The agents' distribution is considered in the last period $T = 100$. Clearly, due to self-organization and learning, the agents can be distributed in small groups of one, two,

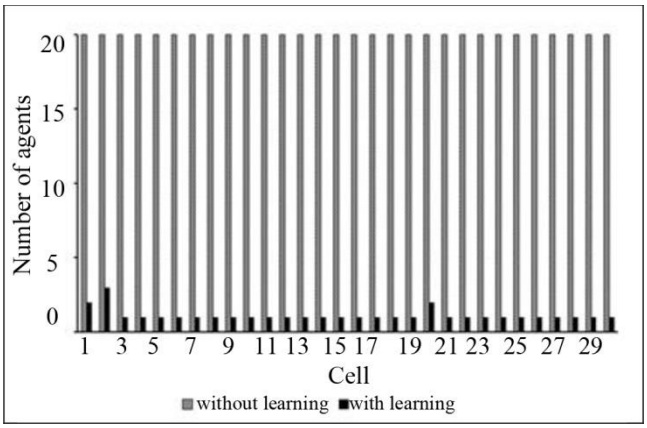


Fig. 8. Distribution of agents in cells: $N = 20$ agents and $M = 30$ cells.

or three agents per cell. In contrast, in the mode without learning, each agent allocates a share of his resource to each cell available. Moreover, more agents select more efficient cells. (In the experiment under consideration, these are cells 1, 2, and 20.)

Consider mode 2 (with learning) to investigate the agents' distribution in cells when there are more cells than agents ($M = 10$ and $N = 5$). The resulting distribution is presented in Table 1. The rows are sorted in the descending order of the initial resource of the agents.

Due to self-organization, the agents select disjoint cells; see the last column. In addition, two agents (2 and 3) allocate their resources to several cells. Note that agent 3, having the smallest initial resource, chooses less efficient cells with a smaller value of the product k_iR_{i0}. According to Table 1, all other agents select cells with a greater value of this product. At the same time, the agent with the maximum initial resource has a better chance of capturing a more efficient cell in the competition. The agent with the least resource (in this experiment, agent 3) obtains less efficient cells. Despite this fact, as the result of the operation of the entire community, the total resource of agent 3 becomes greater compared to agent 5 choosing the most efficient cell. This phenomenon can be explained as follows. Agent 3 allocates resources to a larger number of cells, and since none

Table 1

Distribution of agents in cells

Agent	Agent's initial resource	Efficiency of cells selected by agent	Cell resource	Cells selected by agent
5	0.94	0.97	0.72	7
1	0.54	0.57	0.99	9
2	0.48	0.66. 0.64	0.67. 0.83	2, 3
4	0.33	0.91	0.27	10
3	0.25	0.86. 0.08. 0.02. 0.23. 0.15	0.24. 0.21. 0.73. 0.92. 0.96	1, 4, 5, 6, 8

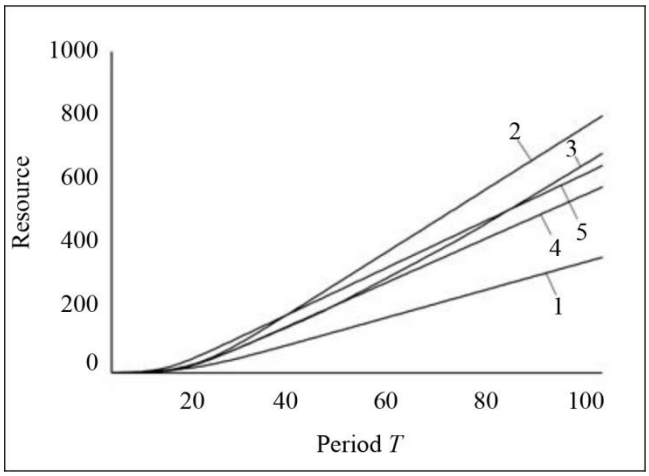


Fig. 9. Dynamics of agents' resources in mode 2, N = 5 and M = 10.

else chooses these (less efficient) cells, the entire resource generated by these cells is taken by agent 3. The results are shown in Fig. 9, where curves 1–5 indicate the resources of the corresponding agents from Table 1.

Thus, *learning and iterative information exchange* reduce the number of agents in a separate cell due to their competition. The agents with a greater initial resource choose more efficient cells, i.e., the ones with higher estimates in the iterative process. Since the new resource generated by a cell is distributed among all agents proportionally to their contributions to it, the agent with the greatest contribution will have the maximum return. Accordingly, his belief to this cell will increase more compared to the other agents allocating their resources to it. The situation described above will be repeated in the next period: it will be beneficial for other agents to choose less efficient displaces all other agents from a more efficient cell. The rest of them are distributed in the remaining cells, considering their estimates during the iterative information exchange. This case applies to a situation when there are significantly more cells than agents. If the numbers of cells and agents coincide, one or more agents may stay in more efficient cells.

Also, an interesting case is when all cells have the same efficiency and the same resource. For example, let these values be equal to 0.9 for all agents, N = 5, and M = 10. The observations were carried out for the period T = 100. According to the simulation results, the agents cannot be distributed in cells. Each agent allocates a share of his resource to each of the available cells. This effect occurs because all estimates and degrees of belief are the same, and each agent allocates his resource uniformly to all possible cells. This problem can be solved by randomizing the initial degrees of belief d_{ij}. Then the simulation results show that the agents are singly distributed in each cell. In this case, the competition is specified through the degrees of belief: it does not matter which cell an agent chooses. For clarity, Table 2 presents the belief matrix of the agents obtained in the last period T = 100. Clearly, each cell contains one agent (see the last column of Table 2). However, some agents select several cells, e.g., agents 1, 4, and 5.

Figure 10 shows the total resource of the agents' community depending on the period T in the two cases described. Clearly, when the agents are distributed singly in each cell, the total resource of the entire community is higher.

Table 2

Belief matrix of agents

Cell	Agent					Number of agents
	1	2	3	4	5	
1	0.00	0.00	0.00	0.00	**0.52**	**1**
2	0.00	0.00	0.00	0.00	**0.52**	**1**
3	0.00	**0.52**	0.00	0.00	0.00	**1**
4	0.00	0.00	0.00	**0.52**	0.00	**1**
5	0.00	0.00	**0.52**	0.00	0.00	**1**
6	0.00	0.00	0.00	0.00	**0.52**	**1**
7	0.00	0.00	0.00	**0.52**	0.00	**1**
8	**0.52**	0.00	0.00	0.00	0.00	**1**
9	0.00	0.00	0.00	0.00	**0.52**	**1**
10	**0.52**	0.00	0.00	0.00	0.00	**1**
Number of cells	2	1	1	2	4	10

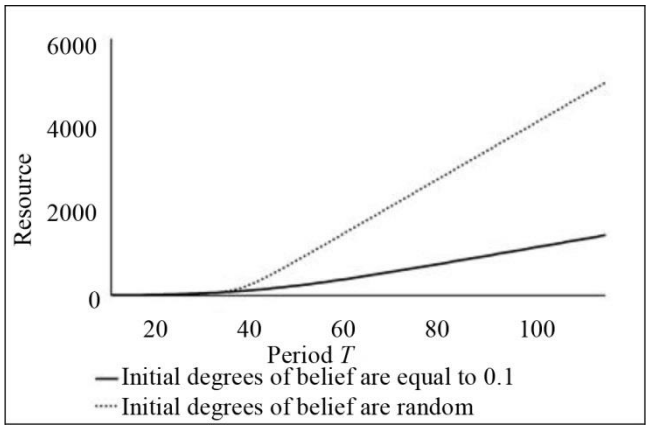


Fig. 10. Dynamics of agents' resources in mode 2 with N = 5, M = 10, and k_i = 0.9.

We also examined the effect of significant parameters (the learning rate β and the "forgetting" parameter γ) on the model's behavior.

Figure 11 shows the community's total resource depending on the "forgetfulness" parameter γ for β = 1.0 in the period T = 100. The best results were observed for β = 1.0 and γ = 0.8.

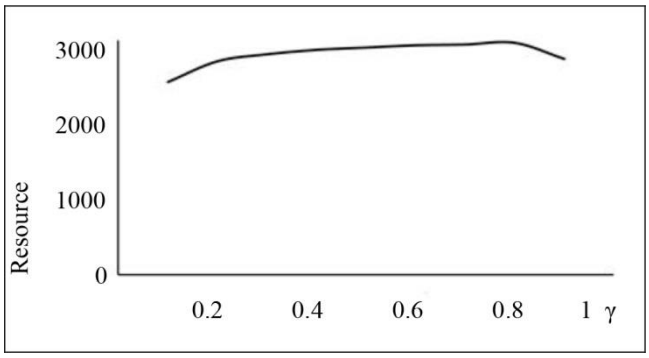


Fig. 11. Community's total resource in mode 2 depending on parameter γ for β =1.0.

CONCLUSIONS

The previous research into collective behavior processes [12–14] was focused on the interaction of different agents (investors and producers) in a transparent environment. Simultaneously, a simple attempt was made to learn investors by adjusting their degrees of belief to producers. However, this attempt was unsuccessful: learning did not significantly increase the resource of the economic community. In this paper, the previous versions of the models have been developed. The rule of interaction between the model's elements (particularly between cells and agents) has been modified by introducing an additional consumption of the agent's resource for interaction with other agents. As a result, the agent's learning has become effective.

According to the computer experiments presented above, this version of the model is operational. An important result of this paper is that under learning and iterative information exchange, the agents are distributed so that their number in each cell is small, and the total resource accumulated by the entire community is higher than in the model without learning and iterations.

The proposed algorithm can be applied to collective behavior problems. The developed model can also be used to study competition and cooperation in economic and social sciences, in which these categories play an important role.

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REFERENCES

1. Shoham, Y. and Leyton-Brown, K., *Multiagent Systems: Algorithmic, Game-Theoretic, and Logical*, Cambridge University, 2008.
2. Tesfatsion, L., Agent-based Computational Economics: Growing Economies from the Bottom up, *Artificial Life*, 2002, vol. 8, no.1, pp. 55–82.
3. Claes, R., Holvoet, T., and Weyns, D., A Decentralized Approach for Anticipatory Vehicle Routing Using Delegate Multiagent Systems, *IEEE Transactions on Intelligent Transportation Systems*, 2011, vol. 12, no. 2, pp. 364–373.
4. Holvoet, T. and Valckenaers, P., Exploiting the Environment for Coordinating Agent, Environments for Multi-Agent Systems III, in *Lecture Notes in Artificial Intelligence*, 2007, vol. 4389, pp. 51–66.
5. Gorodetskii, V.I., Self-Organization and Multiagent Systems: I. Models of Multiagent Self-Organization, *Journal of Computer and System Sciences International*, 2012, vol. 51, no. 2, pp. 256−281.
6. Gorodetskii, V.I., Self-Organization and Multiagent Systems: II. Applications and the Development Technology, *Journal of Computer and System Sciences International*, 2012, vol. 51, no. 3, pp. 391−409.
7. Ashby, W., Principles of the Self-Organizing Dynamic System, *Journal of General Psychology*, 1947, vol. 37, pp. 125−128.
8. Tarasov, V.B., *Ot mnogoagetnykh sistem k intellektual'nym organizatsiyam: filosofiya, psikhologia, informatika* (From Multi-agent Systems to Intelligent Organizations: Philosophy, Psychology, Informatics), Moscow: URSS, 2002. (In Russian.)
9. Karpov, V.E., Karpova, I.P., and Kulinich, A.A., *Sotsial'nye soobshchestva robotov: Emotsii i temperament robotov. Obshchenie robotov. Modeli kontagioznogo, podrazhatel'nogo i agressivnogo povedeniya robotov. Komandnoe povedenie robotov i obrazovanie koalitsii. Prostranstvennaya pamyat' animate* (Social Communities of Robots: Emotions and Temperament of Robots. Communication of Robots. Models of Contagious, Imitative, and Aggressive Behavior of Robots. Team Behavior of Robots and the Formation of Coalitions. Spatial Memory of the Animat), Moscow.: LENAND, 2019. (In Russian.)

10. Demazeau, Y. and Müller, J.-P., *Decentralized A.I.*, North-Holland: Elsevier Science, 1990.
11. Axelrod, R., *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*, Princeton: Princeton University Press, 1997.
12. Red'ko, V.G. and Sokhova, Z.B., Processes of Self-Organization in the Community of Investors and Producers, *Selected Papers from the 19th International Conference on Neuroinformatics*, October 2–6, 2017, Moscow, Russia, 2017, vol. 736, pp. 163−169.
13. Red'ko, V.G. and Sokhova, Z.B., Iterative Method for Distribution of Capital in Transparent Economic System, *Optical Memory & Neural Networks (Information Optics)*, 2017, vol. 26, no. 3, pp. 182−191.
14. Sokhova, Z.B. and Red'ko, V.G., Modeling of Searching for Investing Solutions by Autonomous Agents in a Competitive Transparent Economy, *Artificial Intelligence and Decision Making*, 2019, no. 2, pp. 98–108. http://www.aidt.ru/index.php?option=com_content&view=article&id=841:z-b-sokhova-v-g-redko-modelirovanie-poiska-investitsionnykh-reshenij-avtonomnymi-agentami-v-prozrachnoj-konkurentnoj-ekonomike&catid=366:mnogoagentnye-sistemy&Itemid=211&lang=ru (In Russian.)
15. Bloomeld, R. and O'Hara, M., Market Transparency: Who Wins and Who Loses? *Review of Financial Studies*, 1999, vol. 12, no. 1, pp. 5–35.

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