Competition and Cooperation Mechanisms for Collective Behavior in Large Multi-Agent Systems

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Abstract. We consider a 2-dimensional discrete space modeled by Cellular Automata consisting of $m \times n$ cells that can be occupied by agents. There exist several types of agents which differ in their way of behavior related to their own strategy when they interact with neighbors. We assume that interaction between agents is governed by a spatial Prisoner's Dilemma game. Each agent participates in several games with his neighbors and his goal is to maximize his payoff using own strategy. Agents can change their strategies in time by replacing their own strategy with a more profitable one from its neighborhood. While agents act in such a way to maximize their incomes we study conditions of emerging collective behavior in such systems measured by the average total payoff of agents in the game or by an equivalent measure–the total number of cooperating players. These measures are the external criteria of the game, and players acting selfishly are not aware of them. We show experimentally that collective behavior in such systems can emerge if some conditions related to the game are fulfilled. We propose to introduce an income-sharing mechanism to the game, giving a possibility to share incomes locally by agents. We present the results of an experimental study showing that the sharing mechanism is a distributed optimization algorithm that significantly improves the capabilities of emerging collective behavior measured by the external criterion of the game.

Keywords: Collective behavior; Competition; Distributed optimization; Income sharing; Multi-agent systems; Spatial Prisoner's Dilemma game.

1 Introduction

Competition and cooperation are the two most observed phenomena in the world of the living organisms (people, animals, insects, viruses). Organisms compete for living space, food, rights for reproduction, and other goods to maximize their own income defined in some way. While the personal income maximization of a member of a society is a driving force for the existence of a society, the

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productivity (welfare) of a society measured by the total income is an important measure of the efficiency of a society. The selfish behavior of individuals usually leads to improvements both in personal income and in welfare, but if the level of competition is not adequate for a real situation it may lead to a significant decrease in personal and societal measures of welfare. We can observe that in such situations, the phenomenon of cooperation often emerges and results in an improvement of personal and societal welfare measures due to lower risk and a higher level of stability.

The recent advances in modern computer-communication technologies (e.g. IoT systems, fog/edge/cloud computing systems [12]) oriented toward collecting and processing information by a vast number of simple units unexpectedly show similarities with the natural social systems and that many problems related to providing high performance of these distributed systems can be solved by applying mechanism observed in social systems. Therefore, we propose to consider and study a framework based on a large-scale multi-agent system approach, where agents are capable of solving problems in a distributed way. We believe that the results of the study can be used directly for solving management problems in distributed systems with a massive number of components. The principle requested from such multi-agent systems is the ability of collective behavior which emerges as a result of local interactions of a considerable number of simple components (see, e.g.[4]).

In this paper, we will consider a multi-agent Cellular Automata (CA) – based system working in the framework of CA [11], where an interaction between players is described in terms of non-cooperative game theory [6] using the Spatial Prisoner's Dilemma (SPD) game. We will expect a global collective behavior in such a system measured by the total number of cooperating players, i.e., maximizing the average total payoff of agents of the system. The phenomenon of emerging cooperation in systems described by the SPD game has been a subject of current studies [1, 7]. They show that it depends on many factors, such as payoff function parameters, the type of learning agent, or the way of interaction between agents.

Recently we have shown [10] that the second-order CA based on the concept "adapt to the best neighbor" [5] can be successfully applied as simple learning machines in solving problems of collective behavior. In this paper, we extend a set of agents with different types of behavior and apply a new mechanism of interaction between players, based on the possibility of a local income sharing by agents participating in the game. Our objective is to study the conditions of emerging collective behavior in such a system with local income sharing, i.e., its ability to maximize the average total income in a distributed way.

The structure of the paper is the following. In the next section, SPD game is presented and discussed in the context of collective behavior. Section 3 contains a description of the CA-based multi-agent system acting in the SPD game environment. Section 4 presents a basic mechanism of the game, including income sharing. Section 5 presents some results of the experimental study, and the last section concludes the paper.

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2 Iterated Spatial Prisoner's Dilemma Game and Collective Behavior

We consider a 2D spatial array of size $m \times n$. We assume that a cell (i, j) will be considered as an agent–player participating in the SPD game [3, 5]. We assume that a given player's neighborhood is defined in some way (see, the next Section). Players from this neighborhood will be considered opponents in the game. At a given discrete moment, each cell can be in one of two states: C or D. The state of a given cell will be considered as an action C (cooperate) or D (defect) of the corresponding player against an opponent from its neighborhood. The payoff function of the game is given in Tab. 1.

Table 1: Payoff function of a row player participating in SPD game.

Player's Action	Opponent's Action	
	Cooperate (C)	Defect (D)
Cooperate (C)	$R = 1$	$S = c$
Defect (D)	$T = b$	$P = a$

Each player playing a game with an opponent in a single round (iteration) receives a payoff equal to R, T, S or P, where $T > R > P > S$. We assume that $R = 1$, $T = b$, $S = c$, and $P = a$, and values of a, b and c can vary depending on the purpose of an experiment.

Let us consider the game with the following values of the payoff table parameters: $R = 1$, $b = 1.4$, $c = 0$, and $a = 0.3$. If a player (i, j) takes action $s_{ij} = C$ and the opponent (i_k, j_k) from a neighborhood also takes action $s_{i_k j_k} = C$, then the player receives payoff $u_{ij}(s_{i,j}, s_{i_k j_k}) = 1$. If the player takes the action D and the opponent player still keeps the action C, the defecting player receives payoff equal to $b = 1.4$. If the player takes the action C while the opponent takes action D, the cooperating player receives payoff equal to $c = 0$. When both players use the action D, then both receive payoff equal to $a = 0.3$.

It is worth noticing that choosing by all players the action D corresponds to the Nash equilibrium point (NE) [6], and it is considered a solution to the one–shot game. Indeed, if all players select the action D, each of them receives a payoff equal to a, and there is no reason for any of them to change the action to C while the others keep their actions unchanged because it would result in decreasing its payoff to value 0.

We assume that players are rational and act in such a way to maximize their payoff defined by the payoff function. To evaluate the level of collective behavior achieved by the system, we will use an external criterion (not known for players) and ask whether it is possible to expect from players selecting such

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actions s_{ij} which will maximize the average total payoff (ATP) $\bar{u}()$ of the whole set of players:

$$\bar{u}(s_{11}, s_{12}, ..., s_{mn}) = \frac{1}{mn} \sum_{j=1}^{m} \sum_{i=1}^{n} \sum_{k=1}^{n_{ij}} u_{ij}(s_{ij}, s_{i_k j_k})/n_{ij}, \tag{1}$$

where n_{ij} is the number of opponents in the neighborhood.

Game theory predicts the behavior of players oriented towards achieving NE, i.e., choosing the action D by all players. ATP at NE is equal to a, and we will call it the price of NE. In our game example, this value of ATP is low and equal to $a = 0.3$. The maximal value of ATP is equal to $R = 1$ and corresponds to selecting by all players the action C. We will call this value of ATP the *maximal price point*. The set of players' actions corresponding to the maximal price point is not NE; therefore, it is challenging to expect to reach global cooperation. The purpose of this study is to discover conditions for the emergence of a high level of cooperation between players in iterated spatial games.

3 CA–based Players

Cells (i, j) of a 2D array are considered as CA–based players. At a given discrete moment t, each cell is either in state D or C, which is used by the player as an action with an opponent player. Initial states of CA cells are assigned randomly according to a predefined probability of initial cooperation. For each cell, a local neighborhood is defined. We apply a cyclic boundary condition to avoid irregular behavior at the borders. We will assume the Moore neighborhood with eight immediate neighbors. It means that each player has eight ($N_k = 8$) opponents in the game.

At discrete moments, CA–based players will use their current states as actions to play games with opponents, they will receive payoffs, and next they will change their states applying *rules* (also called *strategies*) assigned to them. We will be using some set of socially motivated rules among which one of them will be initially randomly assigned to a given CA cell, so we deal with a non-uniform CA.

We will consider the following set of six rules: *all–C*: always cooperate; *all–D*: always defect; *k–D*: cooperate until not more than k neighbors defect, otherwise defect; *k–C*: cooperate until not more than k neighbors cooperate, otherwise defect; *k–DC*: defect until not more than k neighbors defect, otherwise cooperate; *pC*: cooperate with probability p_C.

The parameter k plays the role of a threshold of tolerance, and each player using a strategy with tolerance k has its personal value that is assigned initially according to some predefined scheme, and it has a value within the range $0 \leq k \leq 7$. The probability p_C for the strategy pC is defined as a random number from the range $[z - \triangle, z + \triangle]$, where z and $\triangle$ are predefined parameters and $0 < p_C < 1$ and $0 \leq \triangle \leq 0.5$.

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4 Competition and Income Sharing Mechanisms

To study the possibility of the emergence of CA-based players' global collective behavior, we will modify the concept of CA and introduce some local mechanisms of interaction between players.

The first mechanism is *competition* that is based on the idea proposed in [5]. It is based on the principle "adapt to the best neighbor" and differs from the classical concept of CA. It assumes that each player associated with a given cell plays in every single round a game with each of its neighbors, and in this way collects some total score. If the competition mechanism is turned *on*, after q number of rounds (iterations), each agent compares its total payoff with the total payoffs of its neighbors. If a more successful player exists in the neighborhood, this player replaces its own rule with the most successful one. This mechanism converts a classical CA into a *second–order* CA, which can adapt in time.

The second mechanism called *income sharing mechanism* (ISM) that we propose provides a possibility of sharing payoffs by players in a neighborhood. Hard local sharing based on mandatory sharing was successfully used [8] in the context of 1D evolutionary and learning automata games. Here we propose soft sharing, where a player decides to use it or not on the base of competition for income. It is assumed that each player has a tag indicating whether it wishes (*on*) or not (*off*) to share its payoff with players from the neighborhood. The sharing works in such a way that if two or more players from a neighborhood wish to share, each of them: (a) calculates an amount of his payoff $u_{ij}^{to\_send} = u_{ij}()/(1 + n_{ij}^k)$, where n_{ij}^k is a number of neighbors with tags *on*, to send to these neighbors, (b) sends this amount to corresponding neighbors, (c) receives from the corresponding parts of their payoffs. Before starting the iterated game, each player turns on its tag with a predefined probability p_{shar}. Due to the competition mechanism, the most successful rules, together with their tags containing information about willing (or not willing) to share incomes, are spreading over the system during its evolution.

5 Experimental Results

The purpose of the conducted experiments was to find out what are possibilities of emerging collective behavior in the large multi-agent systems when different subsets of strategies are used in the game, and in particular the influence of the ISM mechanism. A 2D array of size 100×100 with 10 000 alive cells was used, with an initial state C or D (player actions) of each cell set with a probability of 0.5. Strategies were assigned initially to CA cells with equal probabilities, except for an experiment with the full set of strategies, where the strategy pC was assigned with a probability equal to 0.001 and the remaining strategies with equal probabilities. To an agent with a "k" rule, an integer value k was randomly selected from the range $[0 \dots 7]$. When an agent was using the strategy pC the probability of cooperation p_C was defined as a real random number from the range $[z - \triangle, z + \triangle]$, where z and $\triangle$ are predefined parameters and the values $z = 0.5$ and $\triangle = 0.4$ were used.

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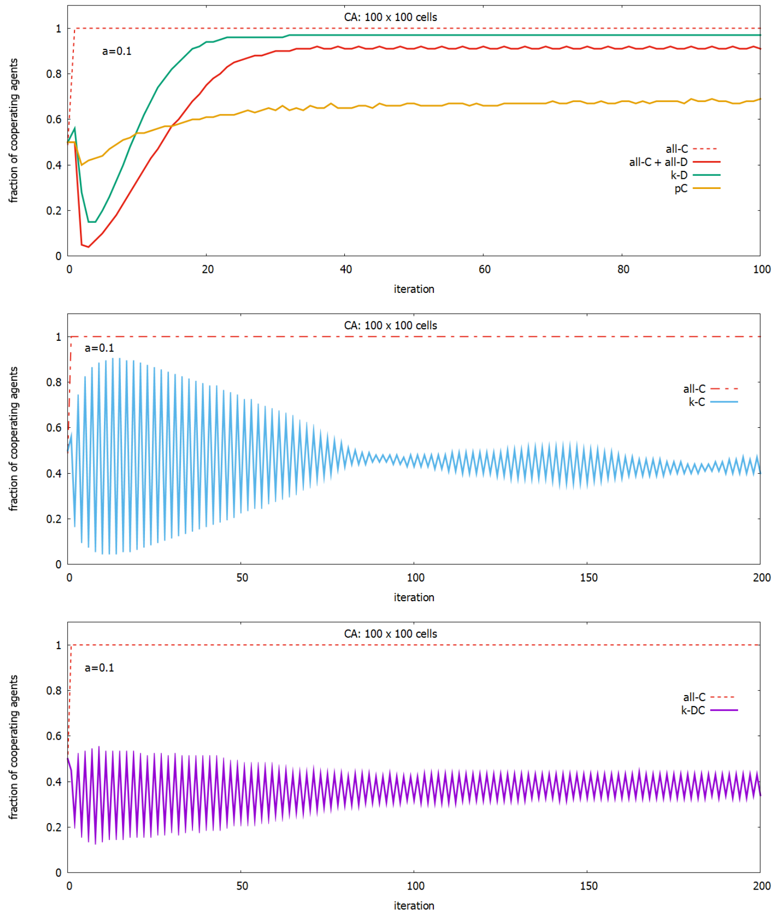

Fig. 1: Fraction of cooperating agents in games with a single adaptive strategy: strategies $\{all\text{–}C + all\text{–}D\}$, $k\text{–}D$ and p_C (upper), strategy $k\text{–}C$ (middle), and strategy $k\text{–}DC$. (lower).

Experiments were conducted with the following parameters of the payoff function: $b = 1, 2$, $c = 0$ and the parameter a was a subject of change. Updating rules of agents by the competition mechanism was conducted after each iteration ($q = 1$). The number of iterations of each run lasted from 100 to 1500 depending on the current set of parameters. When it was necessary, the results presented below were averaged on the base of 20 runs.

5.1 Competition in Systems with a Single Adaptive Strategy

The purpose of the first set of experiments was to see what is the behavior of the multi-agent system when it is homogenous, i.e. all agents use the same adaptive

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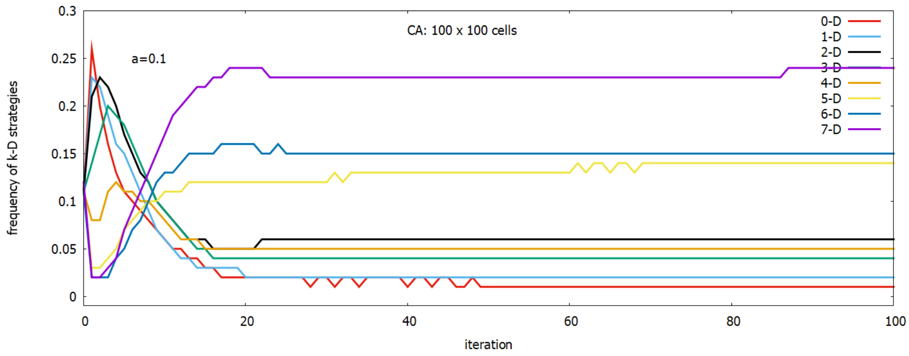

Fig. 2: Evolution of the distribution of the strategies *0–D, 1–D, ... 7–D* when the initial strategy *k–D* is applied.

strategy from the set of the 6 available strategies, and results for single runs (for $a = 0.1$) are shown in Figs. 1 and 2. One can notice that rules *all–C* and *all–D* considered separately are not adaptive, while their combination {*all–C* + *all–D*} is adaptive. On the other hand, the single rule *all–C* can be considered as some theoretical reference to desired optimal behavior of the system. If all agents applied *all–C* then the value of ATP (see, Eq. 1) would achieve its maximum equal to 1, which would results in the maximal number of cooperating agents (see, Fig. 1, dotted line in red).

Fig. 1 (upper) shows levels of a global collective behavior measured by a frequency of cooperating agents applying one of the 3 adaptive strategies: *all–C* + *all–D*, *k–D* or *pC*. One can see that none of them provides the theoretically optimal level of cooperation, but the closest to the optimum is *k–D* (in green), followed by *all–C* + *all–D* (in red), and *pC* (in orange). Fig. 2 gives some explanation of the highest performance of the *k–D* strategy presenting the distribution of the final frequencies related to the value of k. Fig. 2 gives some explanation of the highest performance of the *k–D* strategy presenting the evolution of the distribution of the frequencies related to the value of k (see the final frequencies values). The key factor of the high level of cooperation is a high level of tolerance for defecting neighbors. One can see that the population of agents is dominated by agents having strategies *7–D* (in violet), *6–D* (in blue), and *5–D* (in yellow) highly tolerating defection. The final frequencies of the remaining strategies are equal to or close to 0. Fig. 1 (middle and lower) shows levels of a global collective behavior of two remaining adaptive strategies: *k–C* and *k–DC*. One can see that the behavior of multi-agent systems with any of these two strategies has two phases: the phase with high oscillation of the frequency of cooperating agents, and the phase of reaching some equilibrium with the value of frequency of cooperating agents far from the optimum. We can judge that these strategies can not be used directly as single ones for achieving a high level of collective behavior.

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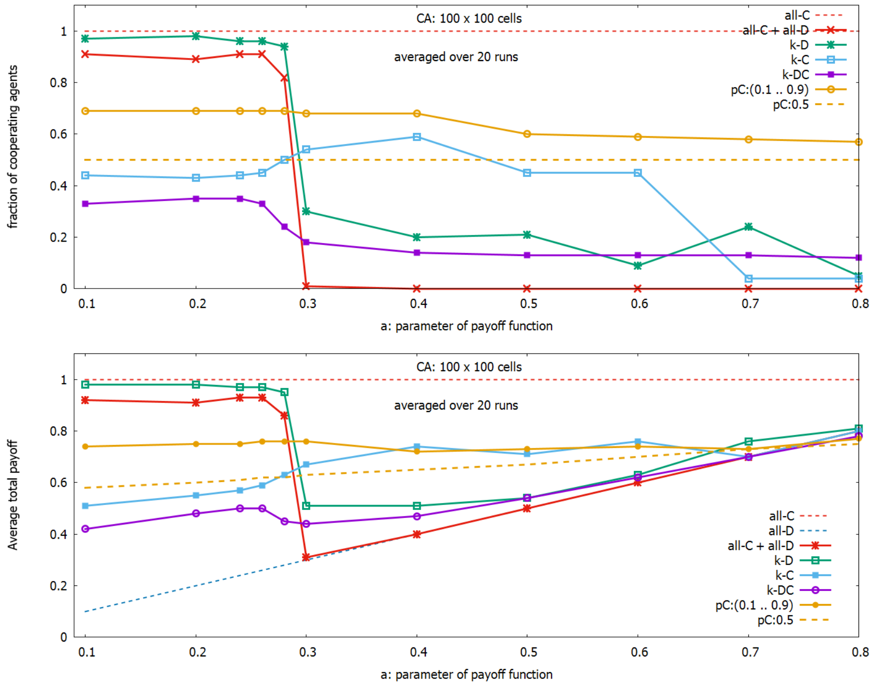

Fig. 3: Behavior of players in games with a single adaptive strategy for different values of the parameter a: fraction of cooperating players (upper), average total payoff of players (lower).

Fig. 3 (upper) shows (results averaged on 20 runs) how the level of cooperation in the multi-agent system with the above considered adaptive rules depends on the value a of the payoff function, and Fig. 3 (lower) presents the corresponding values of ATP. One can see that the highest level of cooperation close to 97% is achieved when players use the strategy k–D for the values of a from the range (0,...,0.26). We can notice a similar behavior of the system when the strategy *all–C* + *all–D* is used, with a lower level of cooperation close to 91%. However, for $a \geq 0.3$ we can see a strong drop of the levels of cooperation, especially for *all–C* + *all–D* when cooperation disappears. For the remaining strategies, the performance of the system in the range (0,...,0.25) is significantly lower than for the first two strategies. For $a \geq 0.3$ we can also observe a drop in the level of cooperation for these strategies, but the level of cooperation remains only slightly lower, and in the case of k–C we can see some improvement in the level of the cooperation.

We can better understand the behavior of players by looking at Fig. 3 (lower) presenting values of ATP of the system as a function of the parameter a, which defines a payoff when two players participating in the game defeat. It is necessary to remember that players take their decisions only based on their personal

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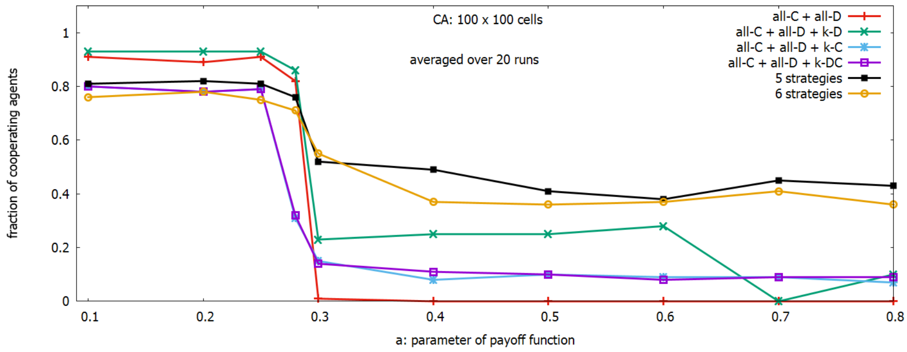

Fig. 4: Fraction of cooperating agents with different sets of strategies as a function of the parameter a.

payoffs, and the value of ATP characterizes the performance of the whole team of players and is not known for them. We can see that in the range (0,..,0.25) of a ATP changes similarly to the frequency of cooperation of players, and depending on an applied strategy is very high or relatively high. In the range (0.25,...,0.3) of a, we can observe a strong fall of ATP, and for $a > 0.3$ we can observe ATP increasing, when at the same time the frequency of cooperation of players is decreasing. This phenomenon can be explained by observing the process of escaping two players from the mutual cooperation when both receive the payoff equal to 1, and coming to a situation when one of them defeats and receives a payoff $b = 1.2$ (the other one still cooperates and receives the payoff equal to 0), which causes defeating also of the second player and results in receiving by both payoffs equal to a, which constitutes a Nash equilibrium point. Due to the nature of NE, returning from it to mutual cooperation is much more difficult than changing mutual cooperation. When the value a is small ($a < 0.25$) escaping from mutual cooperation which leads to NE is not attractive for a player. However, when the value of a increases and players are in NE with a relatively high payoff corresponding to a, returning to mutual cooperation will be more and more problematic. In summarizing, we can see (Fig. 3 (lower)) that ATP, under the given values of a and the remaining parameters of the payoff function, is limited by the maximal value of ATP equal to 1 when all players cooperate (dotted line in red) and the value a (dotted line in blue) corresponding to NE.

5.2 Competition in Heterogeneous Systems

The purpose of the next set of experiments was to study the behavior of the multi-agent system when it is heterogeneous, i.e. agents can use different rules available from a subset of the basic 6 rules, and averaged results (20 runs) are shown in Fig. 4. We considered 3 subsets of strategies consisting of 3 rules: {*all–C* + *all–D* + *k–D* } (plot in green), {*all–C* + *all–D* + *k–C* } (plot in light blue), and {*all–C* + *all–D* + *k–DC* } (plot in violet), a subset with 5 rules {*all–C* + *all–D*

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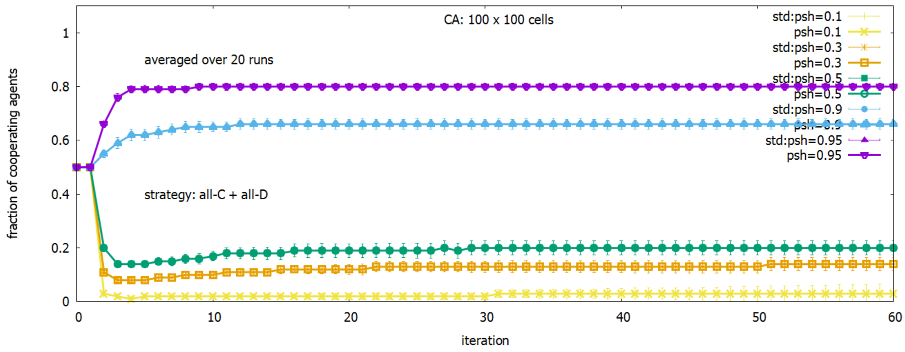

Fig. 5: Games with income sharing ($a = 0.4$): developing of cooperation for different values of an initial value of probability psh of RTS.

+ k–D + k–C + k–DC } (plot in graphite), and a subset with all 6 rules (plot in orange). Like in Fig. 3 we can see similar three regions of a for the behavior of the system, but we can also observe differences. The main differences for the region $a < 0.25$ are the following: (a) the 3 rules subset containing k–D rule (plot in green) is the best performing one, (b) remaining strategies composed of 3, 5 or 6 rules have a good performance, and the 5-rules strategy set (plot in graphite) is the best performing among them, (c) the performance of the 3-rules strategies with rules k–C, k–DC is much higher in comparison when they were used as single adaptive strategies. For $a > 0.3$ we can observe: (a) similar performance of the system composed of 3 rules like it was observed in experiments with single rules, (b) significant increasing of the performance of the system composed of 5 and 6 rules; the increase of the performance is the result of collective behavior caused by including rules k–C and k–DC to the pool, which were not efficient working separately.

5.3 Competition and Cooperation: a Case Study

Results of experiments conducted until now have shown that when the mechanism of competition was used, we could observe a global collective behavior close to the optimal in only some short windows of values of the parameter a under some subsets of agent rules. The main question which arises is the following: can we increase the performance of the system in observed short windows of the parameter a, and probably a much more important question is – whether we can both, significantly extend the window of values of the parameter a to yield a high level of agents' cooperation and also to increase the level of global collective behavior. For this purpose we introduced to the game an additional mechanism – the *income sharing mechanism* (ISM) presented in Subsection 4. We will apply this mechanism to the worst-performing subset of rules *all*–C + *all*–D (see, Fig. 3).

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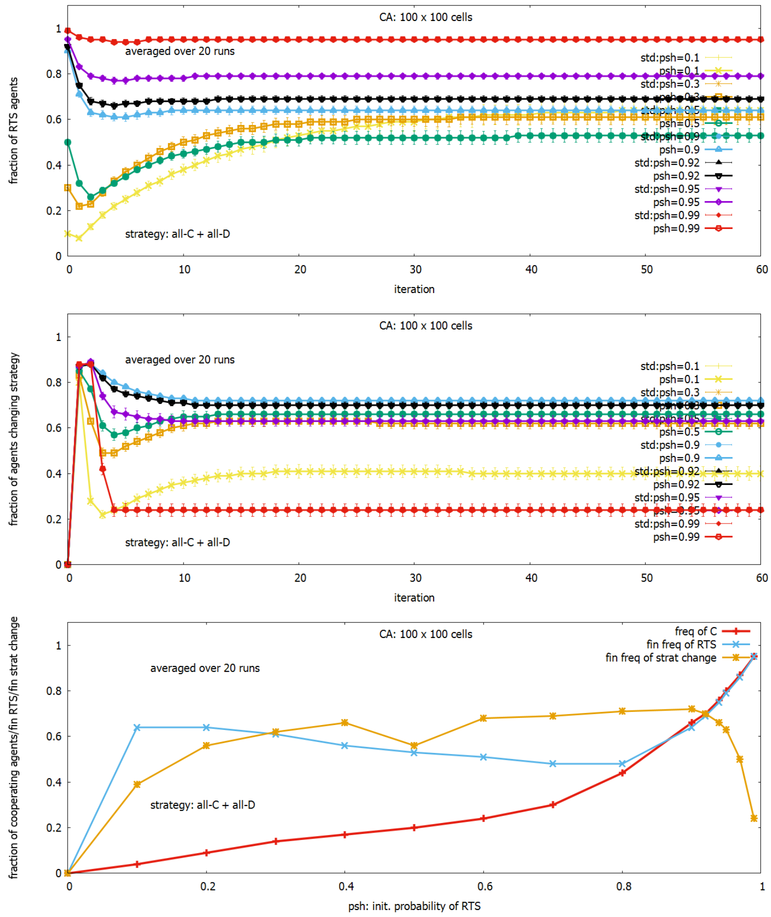

Fig. 6: Games with income sharing ($a = 0.4$): fraction of RTS agents for different values of psh (upper), fraction of agents changing their strategies for different values of psh (middle), final values of the basic income sharing model parameters as a function of psh (lower).

Fig. 5 shows how the fraction of cooperating agents develops in time when the value $a = 0.4$ and ISM are introduced to the game. We can see that the level of global cooperation can be significantly greater than 0 (like it was when ISM was not used) and it ranges from 0.04 to 0.80 and depends on the value of initial probability psh which defines readiness (RTS) of an agent to share income with neighbors. Plots presented in Fig. 6 give some insight into the process of emerging cooperation under ISM.

Fig. 6 (upper) shows how the fraction of RTS agents changes in time and how it depends on psh, Fig. 6 (middle) shows the behavior of the other parameter

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- the frequency of agents changing their strategies due to the local competition between agents, and Fig. 6 (lower) summarizes the influence of these both parameters on developing of cooperation in the system.

We can notice (see, Fig. 6 (upper)) two ways of changing a number of RTS agents which depend on an initial value of probability psh. For $psh < 0.9$ the number of agents wishing to cooperate decreases initially, and after that increases to reach a value from the range (0.53,...,0.66) independently on an initial value of psh. For $a \geq 0.9$ the frequency of RTS agents reaches a high level, lower than the corresponding psh, and it is in the range (0.63,...,0.95). Fig. 6 (lower) shows that RTS frequency (in blue) is slowly decreasing for nearly all ranges of values of psh and depends near linearly on it until reaching the value of psh from the range (0.8,...,0.9). After reaching this area it starts quickly increasing.

Observing Fig. 6 (middle) we can notice two phases of changing the frequency of agents changing their strategies. In the first phase, the value of this parameter grows very fast and independently on the value of psh, and reaches the level around 90% and after that decreases achieving a level depending on psh. Fig. 6 (lower) shows that a value of this parameter (in orange) grows slowly near linearly till around $psh = 0.9$, and after this, it drops very fast, which corresponds to a fast increase of the frequency of cooperation (in red) of agents.

Figs. 7 and 8 give some additional insight into the complex issue of emerging of cooperation of agents caused by ISM. They present final spatial distributions of RTS agents, and final spatial distribution of strategies/states respectively for different values of psh.We already know that a relatively high level of RTS final frequency can be observed for a wide range of values of psh and we can observe it in Figs. 7 (in red) but a strong increase of a level of global cooperation can be observed for $a \geq 0.9$. This figure shows that a reason for this phenomenon can be the spatial structure of agents that do not participate in income sharing. We can observe a significant increase in the level of global cooperation if a block structure of non-sharing agents reaches a high level of granularity when big-size blocks are replaced by a number of small-size blocks distributed over the spatial area of agents.

Fig. 9 summarizes our results concerning the influence of ISM on a global collective behavior. It shows how the frequency of cooperating agents depends on psh for a whole range of the parameter a of the payoff function. We can see a significant extension of a range where a high level of cooperation can be reached, and a near-optimal value of global cooperation can be achieved by introducing ISM, and where this level depends on the value of psh.

6 Conclusions

In this paper, we have studied the conditions of the emergence of collective behavior in large CA-based multi-agent systems with agents interacting according to the principles of SPD games. We have shown that two basic mechanisms - competition and cooperation have the essential importance for the collective behavior of such systems measured by the number of cooperating agents and

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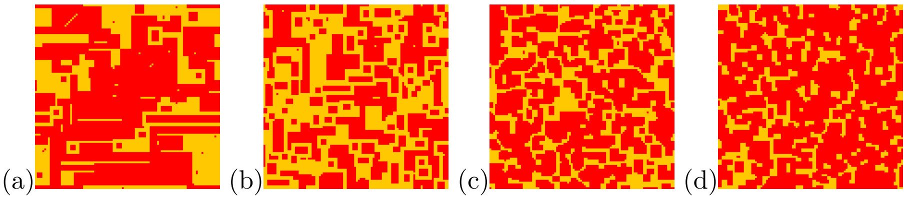

Fig. 7: Distribution of RTS agents (in red) and not RTS agents (in orange) ($a = 0.4$): (a) $psh = 0.1$, (b) $psh = 0.9$. (c) $psh = 0.9$, and (d) $psh = 0.95$.

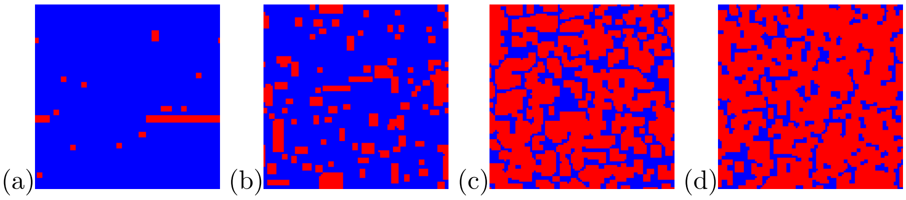

Fig. 8: Distribution of agents strategies/states (*all–C*, in red, *all–D*, in blue) ($a = 0.4$): (a) $psh = 0.1$, (b) $psh = 0.9$. (c) $psh = 0.9$, and (d) $psh = 0.95$.

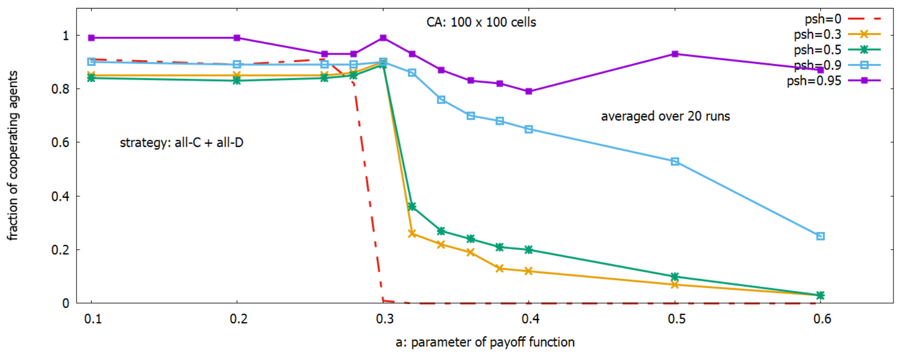

Fig. 9: Games with income sharing: fraction of cooperating agents for different values of *psh* as a function of the parameter *a*.

the average total payoff. While competition provides a high level of collective behavior for systems with a different number of agents' strategies, the level of cooperation can be significantly improved by introducing a mechanism of voluntary income sharing. Our current studies are oriented on recognizing and more deeply understanding processes of emerging cooperation due to income sharing and also on the application of these results for solving optimization problems in

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emerging computer-communication technologies. The concepts of collective behavior of automata were already successfully used to solve problems of scheduling related to cloud computing [2] and lifetime optimization in wireless sensor networks [9].

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