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An Evolutionary Spatial Game-based Approach for the Self-regulation of Social Exchanges in MAS

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Abstract. An open problem in social simulation and MAS applications is the self-regulation of social exchange processes, aiming at the achievement/maintenance of equilibrated exchanges by the agents themselves, providing the continuation of the interactions in time. This paper faces this problem through an approach based on the proposed spatial and evolutionary Game of Self-Regulation of Social Exchange Processes. The agents, adopting different social exchange strategies, which take into account both the short and long-term aspects of interactions, evolve such strategies by themselves in time, in order to maximize their respective strategy-based fitness functions. In consequence, the agents happen to perform more equilibrated and fair interactions, increasing the number of successful exchanges.

1 INTRODUCTION

Social relationships are often described as social exchanges [4]. Interactions in Multiagent Systems (MAS) have been frequently defined as social exchanges [9], which are understood as service exchanges between pairs of agents with the respective evaluation of those exchanges by the agents themselves. [2, 11]

A fundamental problem that has been extensively discussed in the literature is the regulation of such exchanges, in order to allow the emergence of equilibrated exchange processes along the time, promoting the continuity of the interactions [6], social equilibrium [9] and/or fairness behaviour.[4] In particular, this is a difficult problem when the agents, adopting different social exchange strategies, have incomplete information on the other agents' exchange strategies. This is a crucial problem in open agent societies (see [3]).

In our previous work (e.g, [2, 3]), we have developed different models (e.g., centralized/decentralized control, internal/external control, closed/open societies) for the social exchange regulation problem, introducing different hybrid agent models. In particular, in [6], we gave the first step towards the self-regulation of the social exchanges processes. We tackled this problem in a game theory context, given a new interpretation, in terms of material[5] exchanges, to the special kind of interaction described by the evolutionary spatial ultimatum game discussed by Xianyu [12]. Considering an agent society organized in a complex network, we analyzed the evolution of the agents' exchange strategies along the time considering the influence of their social preferences on the emergence of the equilibrium/fairness behavior. However, long-term aspects of the interaction and other concerns that exchange processes may involve were not considered in this simplified model.

This paper finally introduces the *Game of Self-Regulation of Social Exchange Processes*, where the agents, possessing different social exchange strategies, considering both the short and long-term aspects of the interactions, evolve their exchange strategies along the time by themselves, in order to promote more equilibrated and fair interactions, guaranteing the continuation of the exchanges and increasing the number of successful exchanges.[6]

We define the *Game of Social Exchanges*, considering different social exchange strategies (e.g., selfishness, altruism) that establish the exchange behaviours the agents may adopt in their interactions. Then we extend this game to a spatial context, also considering the influence of the other agents' results in any agent's performance (e.g, the agent's tolerance when the benefits it gained in an interaction is less/higher than of its neighboring agents). We consider an incomplete information game, since the agents do not have information about the other agents' exchange strategies. So, any agent has to learn the best strategy it should adopt in its interactions with the other agents of its network in order to increase its fitness value, given by a strategy-based fitness function. We use an evolutionary algorithm for the agents' learning/adaptation process. Considering different scenarios, we analyze the evolution of the agents' exchange strategies in time and the influence of such strategies on the emergence of the equilibrium, continuation and number of successful interactions.

2 SOCIAL EXCHANGES

In Piaget's Theory of Social Exchanges [9], social interactions are seen as service exchanges between pairs of agents, together with the evaluation of those exchanges by the agents themselves, generating material values (the investment value r for performing a service or the satisfaction value s for receiving it) and virtual values (debts t and credits v, which help to keep record of incomplete exchange processes). The agents may possess different social exchange strategies (e.g., altruism, selfishness), when offering services or requesting services from each other, so called strategy-based agents [2, 3].

A *social exchange* between agents i and j involves two types of stages. In stages of type I_{ij}, i offers/realizes a service for j. The *exchange values* involved in this stage are the following: $r_{\mathrm{I}_{ij}}$, which is the value of the *investment* done by i for the realization of a service for j; $s_{\mathrm{I}_{ji}}$, which is the value of j's *satisfaction* due to the receiving of the service done by i; $t_{\mathrm{I}_{ji}}$ is the value of j's *debt*, the debt

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[4] We adopted the concept of fairness behaviour/equilibrium as in [6, 10, 12].
[5] Material exchanges are concerned just with the short-term aspects of the interaction, involving only exchange values generated immediately after the interaction. [2]
[6] For the lack of space, the paper do not present an extensive comparison with the seminal work of Axelrod [1] on the iterated prisoners' dilemma (IPD). Notice, however, that IPD does not refer necessarily to interactions based on the evaluation of service exchanges.

it acquired to i for its satisfaction with the service done by i; and $v_{\mathrm{I}_{ij}}$, which is the value of the *credit* that i acquires from j for having realized the service for j. In stages of type II_{ij}, i asks the payment for the service previously done for j, and the values related with this stage have similar meaning. A *social exchange process* is composed by a sequence of exchange stages of any type. The *material results* (or *balances*), according to the points of view of i and j, are given by the sum of material values of each agent, respectively. The *virtual results* are defined analogously. A society is said to be in equilibrium if the balances of the exchange values are equilibrated for the successive exchanges along the time.

Given an ongoing interaction, the agents may choose to focus their attention either on the material or in the virtual results, in order to analyze that interaction. Material results are important because they report the concrete results obtained from the ongoing interaction at each of its steps, and constitute, thus, the main aspect to qualify such interaction. Virtual results, on the other hand, may be combined with complementary information (e.g. trust) to qualify the possible evolution of the interaction, allowing the agents to make decisions on participating or not in the future steps of the interaction. [3]

3 THE GAME OF SOCIAL EXCHANGES

The two-player Game of Social Exchanges (GSE) is a sequential game of incomplete information, where two agents i, j perform the two stages of a social exchange, generating material and virtual exchange values, according to their respective exchange strategies. A *social exchange strategy* of an agent $\lambda = i, j$ is defined by a tuple

$$(r_\lambda, r_\lambda^{max}, s_\lambda^{min}, k_\lambda^{\rho t}, k_\lambda^{\rho v}), \tag{1}$$

where: $r_\lambda \in [0,1]$ is the actual investment proposal made by the agent λ to the other agent, in a certain exchange stage; $r_\lambda^{max} \in [0,1]$ is the maximum investment value that the agent λ is willing to have for a service performed for the other agent; $s_\lambda^{min} \in [0,1]$ is the minimum satisfaction value that an agent λ accepts; $k_\lambda^{\rho t}$, $k_\lambda^{\rho v} \in [0,1]$ are, respectively, debt and credit depreciation ($\rho = d$) or overestimation ($\rho = o$) factors characterizing each exchange strategy, with:

Depreciation: $t_\lambda = (1-k_\lambda^{dt})s_\lambda$ and $v_\lambda = (1-k_\lambda^{dv})r_\lambda$;
Overestimation: $t_\lambda = s_\lambda + (1-s_\lambda)k_\lambda^{ot}$; $v_\lambda = r_\lambda + (1-r_\lambda)k_\lambda^{ov}$.

Considering incomplete information, the agents do not know the other agents' exchange strategies except for the offers it can receive. Also, when i's service offer is rejected by j, the agent i does not obtain the exact information on j's minimal satisfaction value.

In any exchange stage I_{ij} between strategy-based agents i and j, i offers a service to j, whose related investment value is $r_{\mathrm{I}_{ij}} \leq r_i^{max}$. Whenever the correspondent satisfaction of agent j is such that $s_{\mathrm{I}_{ji}} \geq s_j^{min}$, then this exchange stage happens successfully, and j's debit and i's credit values are generated according to their respective exchange strategies, considering the depreciation/overstimation factors $k_j^{\rho t}$ and $k_i^{\rho v}$, respectively. If the agent i has any credit with agent j then the second exchange stage II_{ij} occurs or not in a similar way, and the correspondent exchange values are generated analogously. Whenever agents i and j, with the respective exchange strategies:

$$(r_{ij}, r_i^{max}, s_i^{min}, k_i^{\rho t}, k_i^{\rho v}) \text{ and } (r_{ji}, r_j^{max}, s_j^{min}, k_j^{\rho t}, k_j^{\rho v}),$$

interacts in a social exchange, the payoff i obtains in this interaction is evaluated by the function $\mathrm{p}_{ij} : [0,1]^4 \to [0,1]$, with

$$p_{ij}(r_{\mathrm{I}_{ij}}, s_{\mathrm{I}_{ji}}, r_{\mathrm{II}_{ji}}, s_{\mathrm{II}_{ij}}) = \begin{cases} \dfrac{1 - r_{\mathrm{I}_{ij}} + s_{\mathrm{II}_{ij}}}{2} & \text{if } (r_{\mathrm{I}_{ij}} \leq r_i^{\max} \wedge s_{\mathrm{I}_{ji}} \geq s_j^{\min}) \\ & \quad \wedge\ (r_{\mathrm{II}_{ji}} \leq r_j^{\max} \wedge s_{\mathrm{II}_{ij}} \geq s_i^{\min}) \\ \dfrac{1 - r_{\mathrm{I}_{ij}}}{2} & \text{if } (r_{\mathrm{I}_{ij}} \leq r_i^{\max} \wedge s_{\mathrm{I}_{ji}} \geq s_j^{\min}) \\ & \quad \wedge\ (r_{\mathrm{II}_{ji}} > r_j^{\max} \vee s_{\mathrm{II}_{ij}} < s_i^{\min}) \\ 0 & \text{if } (r_{\mathrm{I}_{ij}} > r_i^{\max} \vee s_{\mathrm{I}_{ji}} < s_j^{\min}) \\ & \quad \wedge\ r_{\mathrm{II}_{ji}} > r_j^{\max} \vee s_{\mathrm{II}_{ij}} < s_i^{\min}. \end{cases}$$

which considers two exchange stages I_{ij} and II_{ij} between the agents i and j. The payoff of agent j is defined analogously. Observe that the maximal reward that the two interacting agents i and j are allowed to receive happens when the agent i, in the exchange stage I_{ij}, performs a service offer such that $r_{\mathrm{I}_{ij}} \leq r_i^{\max}$ and $s_{\mathrm{I}_{ji}} \geq s_j^{\min}$, and the agent j, in the exchange stage II_{ij}, performs a service offer such that $r_{\mathrm{II}_{ji}} \leq r_j^{\max}$ and $s_{\mathrm{II}_{ij}} \geq s_i^{\min}$.

Whenever an exchange stage does not happen, the values r and/or s may be equal to zero, i.e., if either i or j refuses to interact in any exchange stage then both agents get nothing in that stage.

The GSE was inspired by an interpretation of the ultimatum game (UG) introduced in previous work [6]. Analogously to what was shown in the literature for the UG [12], the *Nash equilibrium* of the game of social exchanges happens when an agent i, in the exchange stage of type I_{ij}, offers a service with the least possible related investment value to agent j, which, in its turn, accepts such offer whenever it does not violate its exchange strategy. Reciprocal behaviours are expected for the agents i and j in a exchange stage of type II_{ij}. If we consider a spatial version of the this game, the same solution is valid for all agents (e.g., see [8, 12], for a spatial version of the UG).

However, analysing practical experiments on the UG (e.g., [5, 7]), it is possible to expect that, in the case of GSE, analogously to what happens in the UG, the agent j will reject the service offer if it believes that the proposal is unfair. When the game is played several times, the offers tend to be more equilibrated, since j may reject bad service offers intending to obtain better proposals in the future [8].

4 THE GAME OF SELF-REGULATION OF SOCIAL EXCHANGE PROCESSES

The *Game of Self-regulation of Exchange Processes* (GSREP) consists in a spatial and evolutionary version of the GSE. In order to maximize an exchange strategy-based fitness function, the agents try to evolve their social exchange strategies along the time, giving rise to more equilibrated exchanges and promoting the continuity of the interactions, so obtaining the self-regulation of exchange processes.

The proposed model consists of a set of social exchange strategy-based agents, organized in a complex network, namely, a Watts-Strogatz (WS) small world, which defines the neighborhood for each agent in the system. In each simulation cycle, each agent interacts with the other agents in its own neighborhood, performing a social exchange game separately with all its neighboring agents. In each neighborhood, the agent presenting the best adaptation result is chosen, in order to construct a new neighborhood, composed by agents coming from different neighborhoods.

Considering a neighborhood $\mathrm{A} = \{1, \ldots, m\}$ composed by m agents, each agent $i \in \mathrm{A}$ plays the exchange game with the other $m-1$ neighboring agents $j \in \mathrm{A}$, such that $j \neq i$. In each simulation cycle, each agent i evaluates its local social exchange material results with each other neighboring agent j, using the local payoff function given in Eq. (2). Then, the total payoff received by each agent is calculated after each agent has performed the two exchange stages with his entire neighborhood. For p_{ij} calculated by Eq. (2), the *total payoff allocation* of a neighborhood of m agents is given by

$$\mathrm{X} = \{x_1, \ldots, x_m\}, \text{ where } x_i = \sum_{j \in \mathrm{A}, j \neq i} p_{ij}. \tag{2}$$

Each agent analyses its social exchange performance via a respective strategy-based fitness function. Then, the agents adjust their social exchange strategies in order to maximize their fitness functions. However, as discussed in the previous sections, the agents possesses no exact information on the strategies adopted by the other agents.

To model the adaptive learning behavior under this situation, we implemented an evolutionary algorithm using NetLogo.

4.1 Exchange Strategy-Based Fitness Function

A *spatial social exchange strategy* considers not only the concerns about the agent itself but also about the others agents. A *spatial social exchange strategy* of an agent λ, $\lambda = 1, \ldots, m$, is defined by a tuple

$$(r_\lambda, r_\lambda^{max}, s_\lambda^{min}, a_\lambda, b_\lambda, k_\lambda^{\rho t}, k_\lambda^{\rho v}), \tag{3}$$

where $r_\lambda, r_\lambda^{max}, s_\lambda^{min}, k_\lambda^{\rho t}, k_\lambda^{\rho v}$ have the same meanings as in Eq. (1), $a_\lambda \in [0,1]$ is the weight that represents λ's tolerance degree when its payoff is less than of its neighboring agents (called *envy degree*), and $b_\lambda \in [0,1]$ represents λ's tolerance degree when its payoff is higher than its neighboring agents' payoffs (called *guilt degree*). In this paper, we considered the following initial social exchange strategies, inspired by [2, 3, 6]:

Altruism: the altruist agent is mostly seeking the benefit of the other agent, accepting exchanges that represent advantages for the other, presenting high r_{alt}^{max} and low s_{alt}^{min}. Also, it has a high tendency to under-evaluate its credits by a high depreciation factor k_{alt}^{dv} and over-evaluate its debts by a high overestimation factor k_{alt}^{ot} . Finally, the agent "suffers" whenever its material results are higher than the material results of the other agents, and this is represented by a high guilt degree b_{alt} and low envy degree a_{alt}.

Selfishness: the selfish agent is precisely opposite to the altruist agent, with low r_{self}^{max}, high s_{self}^{min}, high tendency of under-evaluate its debts by a high depreciation factor k_{alt}^{dt} and over-evaluate its credits by a high overestimation factor k_{self}^{ov}. The agent "suffers" whenever its material results are lower than the other agents, with a low guilt degree b_{self} and a high envy degree a_{self}.

Weak Altruism (Selfishness): agents adopting the altruism (selfishness) exchange strategy but assuming less extreme values.

Rationality: agents caring only with their material results are rational according to Game Theory, so they adopt very low r_λ^{max} and s_λ^{min}, guaranteing non null payoff in each interaction. Also, rational agents neither under-evaluate nor over-evaluate debts and credits, and do not compare their material results with the others.

The social exchange strategies exhibited by the agents are considered in the definition of the so-called strategy-based fitness function, representing the influence of the envy and guilt degrees in the agents' total payoff results. Let X be the total payoff allocation of a neighborhood of m agents (Eq. (2)). The modeling of the *exchange strategy-based fitness function* U_i of an exchange strategy-based agent i, may assume one of five forms encompassed by its general definition:

$$\mathrm{U}_i(\mathrm{X}) = x_i - \frac{a_i}{(m-1)} \sum_{j \neq i} \max(x_j - x_i, 0) - \frac{b_i}{(m-1)} \sum_{j \neq i} \max(x_i - x_j, 0), \tag{4}$$

where x_i is the total payoff of agent i, x_j is the total payoff of a neighboring agent j, a_i and b_i are, respectively, i's envy and guilt degrees, characterizing the five types of exchange strategies.[7]

4.2 The Evolutionary Algorithm for the Agent Exchange Strategy Evolution

Each agent i is defined by a chromosome $[g_i^0, \ldots, g_i^{34}]$ (Table 1), which is the data structure representing a possible solution codified by 35 genes encompassing the social exchange strategy currently adopted by the agent i and the way the agent i evolves such strategy. The elements $g_i^8, \ldots, g_i^{34}$ constitute the the probability vector $g_i^8 = p_i^0, \ldots, g_i^{34} = p_i^{26}$ that adjusts the agent's exchange strategy after each simulation cycle. The probability vector indicates the 27 possible alternatives for modifying some parameters of the spatial exchange strategy, after the analysis of the exchange strategy-based fitness function adopted by the agent i, as shown in Table 2. For example, p_i^0 is the probability that the agent i increases r_i, r_i^{max} and s_i^{min} (by a certain exogenously specified adjustment step); on the other hand, p_i^5 is the probability that the agent i increases r_i, decreases s_i^{min}, whereas r_i^{max} remains unchanged.

Table 1. Chromosome of an agent i

g_i^0	g_i^1	g_i^2	g_i^3	g_i^4	g_i^5	g_i^6	g_i^7	g_i^8	$\cdots$	g_i^{34}
r_i	s_i	r_i^{max}	s_i^{min}	a_i	b_i	$k_i^{\rho t}$	$k_i^{\rho v}$	p_i^0	$\cdots$	p_i^{26}

The agent i chooses an alternative from the corresponding probability vector based on the generated random number in the interval $[0,1]$. Then, i plays with its neighboring agents, adjusting only the values of r_i, r_i^{max} and s_i^{min} accordingly, based on its strategy-based fitness function (the other strategy's parameters are intrinsical to the initially adopted strategy and remain unchanged in the whole process). If the strategy under the current state provides the agent i with more or less benefit than the last simulation cycle, i updates the probability vector to reflect the benefit difference. That is, the agent i increases the probability for the just chosen alternative if its fitness is higher than the previous one. However, if the strategy under the current state provides the agent i with less benefit than the last simulation cycle, the agent i decreases the just chosen probability. To ensure that the sum of the probabilities is equal to 1, other elements in the probability vector are likewise be modified at the same time. Otherwise, the agent i does not change its probability vector.

The probability and strategy adjustment steps f_p and f_s determine, respectively, on which extent the probabilities of the probability vector and the values r_i, r_i^{max} and s_i^{min} are increased or decreased.

Then, the exchange strategies of each agent evolve accordingly and the agents are induced to pursuit of maximum benefit through the evolutionary algorithm-based learning in a simulation process.

5 SIMULATION RESULTS

The simulation is carried out on a WS small world network with 1200 heterogeneous agents, implemented in Netlogo. Each simulation was composed by 5000 cycles[8], which is sufficient to guarantee that the agents' fitness values are no longer improved. We performed 30 simulations, and the values and functions showed in the figures represent the average behavior. For the lack of space, we present just one case of strategy distribution, called P5-all. We adopted the initial parameters of the social exchange strategies shown in Table 3, where $r_{rat}^{max} = \min\{r_{self}^{max}, r_{wself}^{max}, r_{alt}^{max}, r_{walt}^{max}\}$ and $s_{rat}^{min} = \min\{s_{self}^{max}, s_{wself}^{max}, s_{alt}^{max}, s_{walt}^{max}\}$.

Table 3. Parameters of the social exchange strategies

Strategy	r^{max}	s^{min}	a	b	$k^{\rho t}$	$k^{\rho v}$
altruism	0.8	0.2	0.1	0.9	$0.2, \rho = o$	$0.2, \rho = d$
weak altruism	0.6	0.4	0.3	0.7	$0.1, \rho = o$	$0.1, \rho = d$
selfishness	0.2	0.8	0.9	0.1	$0.2, \rho = d$	$0.2, \rho = o$
weak selfishness	0.4	0.6	0.7	0.3	$0.1, \rho = d$	$0.1, \rho = o$
rationality	r_{rat}^{max}	s_{rat}^{min}	0	0	0	0

During the simulations, the effects of the combined social strategies on the evolution of the agent strategies and exchange process are analyzed. The aim is to verify if the agents are capable to evolve their exchange strategies in order to achieve social equilibrium, promoting the continuation of equilibrated exchanges along the time, so achieving the self-regulation of social exchange processes. In the strategy

[7] The fitness function was based on the discussion presented in [6, 12].

[8] The figures show only the first 500 cycles, since we observed that the system is stabilized around 500 cycles.

Table 2. The probability vector adjustment

	r	r^{max}	s^{min}		r	r^{max}	s^{min}		r	r^{max}	s^{min}
p^0	$\uparrow$	$\uparrow$	$\uparrow$	p^9	$=$	$\uparrow$	$\uparrow$	p^{18}	$\downarrow$	$\uparrow$	$\uparrow$
p^1	$\uparrow$	$\uparrow$	$=$	p^{10}	$=$	$\uparrow$	$=$	p^{19}	$\downarrow$	$\uparrow$	$=$
p^2	$\uparrow$	$\uparrow$	$\downarrow$	p^{11}	$=$	$\uparrow$	$\downarrow$	p^{20}	$\downarrow$	$\uparrow$	$\downarrow$
p^3	$\uparrow$	$=$	$\uparrow$	p^{12}	$=$	$=$	$\uparrow$	p^{21}	$\downarrow$	$=$	$\uparrow$
p^4	$\uparrow$	$=$	$=$	p^{13}	$=$	$=$	$=$	p^{22}	$\downarrow$	$=$	$=$
p^5	$\uparrow$	$=$	$\downarrow$	p^{14}	$=$	$=$	$\downarrow$	p^{23}	$\downarrow$	$=$	$\downarrow$
p^6	$\uparrow$	$\downarrow$	$\uparrow$	p^{15}	$=$	$\downarrow$	$\uparrow$	p^{24}	$\downarrow$	$\downarrow$	$\uparrow$
p^7	$\uparrow$	$\downarrow$	$=$	p^{16}	$=$	$\downarrow$	$=$	p^{25}	$\downarrow$	$\downarrow$	$=$
p^8	$\uparrow$	$\downarrow$	$\downarrow$	p^{17}	$=$	$\downarrow$	$\downarrow$	p^{26}	$\downarrow$	$\downarrow$	$\downarrow$

learning process, each agent will search for the best exchange strategy to play the GSREP in order to improve its fitness function, which means also to increase the number of successful exchange stages.

In the first analysed scenario, the agents learned their strategies based only in the analysis of their strategy-based fitness functions. Figures 1 and 2 show the evolution of the number of unsuccessful exchange stages (red), one successful exchange stage (green) and complete successful two-stage interactions (blue) in the initial (250 cycles) and final (5000 cycles) steps of the simulations. Analyzing the behavior of the red curve, we observed that the evolution of the agents' strategies along the time yielded the reduction of the number of unsuccessful interactions. Furthermore, in the initial steps of the simulations, the number of unsuccessful interactions was approximately 230,000 and, at the end of the simulations, such number decreased to approximately 50,000. The green and blue curves increase along the time, that is, the number of interactions with one or two successful exchanges increased.

Figures 3 and 4 show the evolutionary behaviors of the strategy-based fitness functions of each type of strategy-based agent along the time. The blue, light blue, red, pink and black curves represent the behaviors of the fitness functions of the altruist, weak altruist, selfish, weak selfish and rational agents, respectively. Observe that the evolution of the agents' exchange strategies contributed for the increasing of their fitness values along the time. Observe, however, that the exchange strategies achieved a stable configuration after a certain time, since the different exchange strategy-based functions became stable along the time. Moreover, it holds that $\mathrm{U}_{alt} \geq \mathrm{U}_{rat} \geq \mathrm{U}_{walt} \geq \mathrm{U}_{wself} \geq \mathrm{U}_{self}$. Finally, although selfish agents presented the worst performance in social exchange processes, due to the adoption of such non flexible exchange strategy, their fitness values increased along the time, which indicates that selfish agents were capable to evolve their exchange strategies along the time.

Figure 5 shows the number of unsuccessful, one-stage and two-stage successful social exchanges in the first (blue bar) and last (red bar) cycles of the simulation, according to the adopted exchange strategy. In the bottom right graphic, we show the initial and final population size, related to the number of successful exchange stages. Observe that the evolution of the exchange strategies allowed the agents to increase the number of successful exchanges, independently of the initial strategies they have adopted. Tables 4 and 5 show the percentage of the population of each strategy with respect to successful exchange stages, in the first and last cycles, respectively.

Figure 6 presents the initial and final agents' fitness values in the first (blue bar) and last (red bar) cycles of the simulation, respectively, according to the adopted strategy. The average fitness value of altruist agents in the first cycle was 0.1611, and after 5000 cycles, the altruist agents evolved their strategies so that this value reached 0.9298 (an increase of 477 %). The respective adaptation values of weak altruist agents is from 0.1210 to 0.6493 (an increase of 437 %). As expected, the selfish (weak selfish) agents presented negative initial mean fitness value, but, after 5000 cycles, their final mean fitness

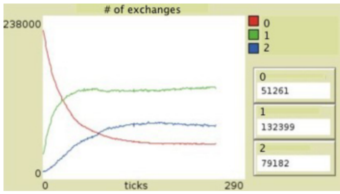

Figure 1. Successful social exchanges stages in 250 cycles

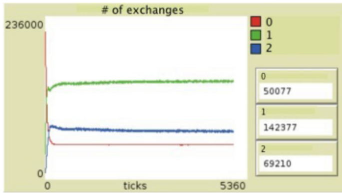

Figure 2. Successful social exchanges stages in 5000 cycles

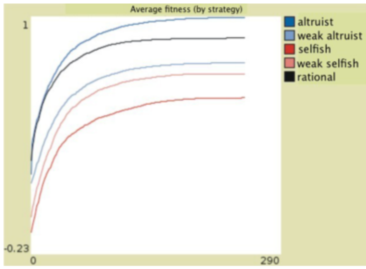

Figure 3. The strategy-based fitness functions in 250 cycles

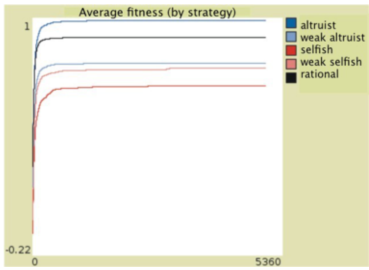

Figure 4. The strategy-based fitness functions in 5000 cycles

value increased to 0.5459 (0.6169). As also expected the highest initial mean fitness value was presented by rational agents (0.2067). However, at the end of the simulation its mean fitness value was 0.6416. The mean global fitness value, considering the entire agent population, in the first and last cycles, was 0.0565 and 0.8388, respectively, representing an increasing of 1,384%, showing that the population was able to adapt along the time, learning and modifying their social exchange strategies in order to promote more equilibrated exchanges and the continuation of the interactions. Table 6 shows the results of means, variances and standard deviations of the fitness values of different social exchange strategies.

Analyzing the results of the number of successful exchange stages

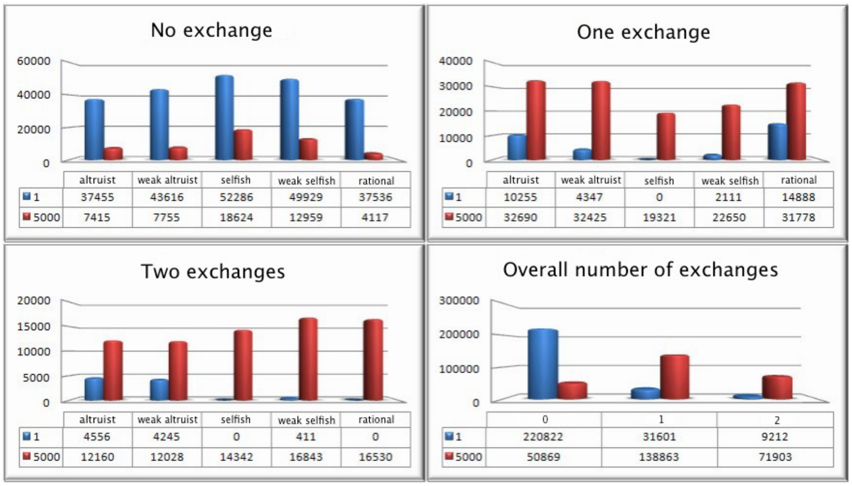

Figure 5. Evolution of the exchanges considering the first and last cycles

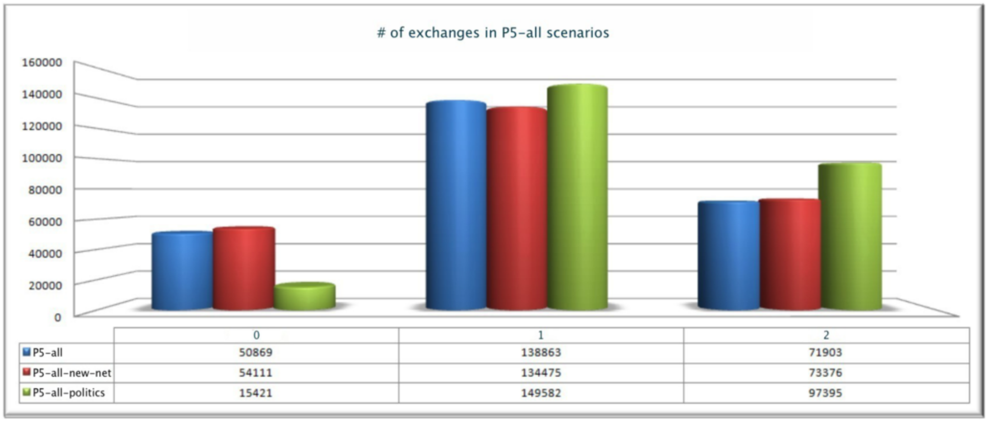

Figure 7. Comparison on the numbers of successful exchange stages obtained in the different scenarios

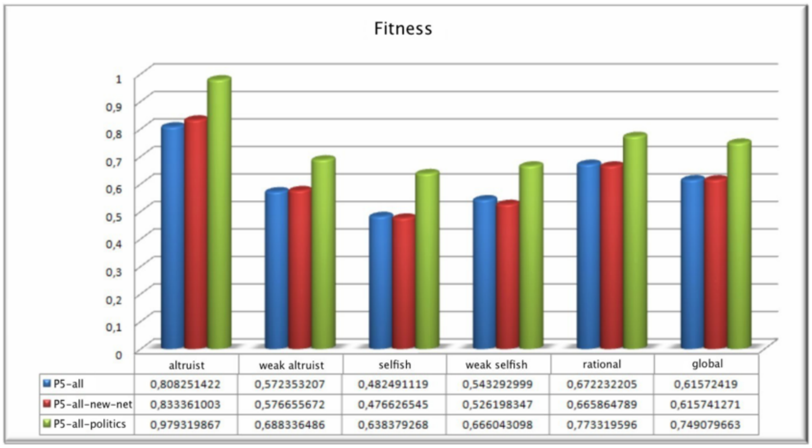

Figure 8. Comparison on the fitness values obtained in the different scenarios

and fitness values, we observed that agents adopting the selfishness-based exchange strategy presented the the worst adaptation behavior. We remark that although they are able to adapt some parameters of their strategy, namely, r_i (the actual service investment proposal), r_i^{max} (the maximal tolerable investment value) and s_i^{min} (the minimal acceptable satisfaction value), the other parameters that are intrinsical to the selfishness-based strategy remain the same (e.g., the high envy degree when the payoffs of the other agents are higher than its own payoff, the high debit depreciation factor and credit overestimation factor). For this reason, selfish agents had more difficult to improve their interactions. However, they did increase the number of successfully performed exchange stages and their fitness values.

On the other hand, for analogous reason, the agents adopting the altruism-based social exchange strategy presented the best adaptation behavior, presenting the highest increasing of the number of successfully performed exchange stages and of their fitness values.

As expected, agents adopting the weak selfishness-based exchange strategy presented better adaption behavior than the agents adopting the pure selfishness-based exchange strategy. Analogously, agents with weak altruism-based strategy presented worse adaption behav-

Table 4. Successful exchange stages in the first cycle (%)

Strategy	none	one	two (complete)
altruism	71.6631	19.6206	8.7163
weak altruism	83.5415	8.3271	8.1314
selfishness	100	0	0
weak selfishness	95.1913	4.0242	0.7845
rationality	71.6005	28.3995	0

Table 5. Successful exchange stages in the last cycle (%)

Strategy	none	one	two (complete)
altruism	14.1873	62.5461	23.2665
weak altruism	14.8544	62.1072	23.0383
selfishness	35.6187	36.9515	27.4296
weal selfishness	24.7058	43.183 0	32.1110
rationality	7.85247	60.6165	31.5309

Table 6. Mean, variance, standard deviation of fitness values

Strategy	Mean	Variance	Standard deviation
altruism	0.808251422	0.002775094	0.052679164
weak altruism	0.572353207	0.000254429	0.015950838
selfishness	0.482491119	0.000590481	0.024299809
weak selfishness	0.543292999	0.000410004	0.020248553
rationality	0.672232205	2.37152E-05	0.004869826
all agents	0.615724190	0.000222439	0.014914377

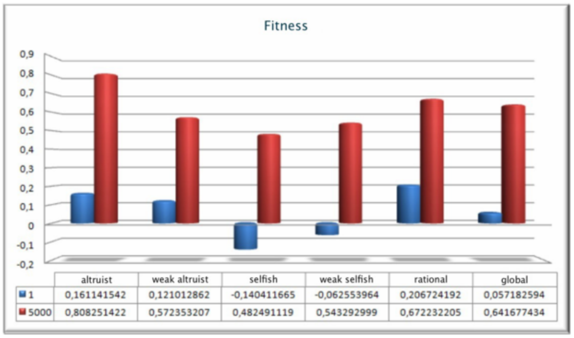

Figure 6. Evolution of the adaptation based on the fitness increasing

ior than the agents with pure altruism-based strategy, although still better than the ones adopting weak selfishness-based strategy.

Finally, rational agents presented an excellent adaptation behavior, only below altruist agents. Even if rational agents are able to adapt only the parameters r_i, r_i^{max} and s_i^{min} of their exchange strategy, the other intrinsical parameters that remain unchanged do not interfere in the evaluation of their fitness value, which only considers the payoffs received in each exchange stage. Then, rational agents improved their interactions, presenting high increasing of the number of successfully performed exchange stages and of their fitness values.

The overall results, concerning the average number of successfully performed exchange stages and fitness value of the entire population, showed that the agents were able to regulate their social exchange processes by themselves, by evolving their exchange strategies at each interaction (simulation cycle). Each agent adapted its own exchange strategy in order to improve its interactions with the other agents, so achieving the self-regulation of social exchange processes.

We also analyse a second scenario (called *new-networks*), where at each 1250 cycles the agents are reallocated according to a random distribution, modifying the network composition, but maintaining its topology. This scenario, representing some kind of mobility, was used in order to analyze if the results are dependent on the neighborhood. In the third scenario (called *politics*), at each 500 simulation cycles, we consider an influence politics, when the averages of the values r_i, r_i^{max} and s_i^{min} of all agents adopting the same strategy become public, and so the agents are "influenced" by those values.

Figures 7 and 8 present a comparison among the results obtained in all scenarios. In Figure 7, the blue, red and green bars represent the number of social exchange stages successfully performed in the first, second and third scenarios, respectively. Similarly, in Figure 8, the bars represent the fitness values obtained in those scenarios, considering the different strategies individually and globally. Observe that the scenario *new-networks* did not contribute for the strategy evolution, since the fitness values did not improve with the agent mobility and the results achieved on the number of successful exchange stages showed no neighborhood dependence. However, the scenario *politics* obtained the best results in relation to the number of successful exchange stages and fitness values, supporting the idea that an influence politics may lead to optimal parameters for each exchange strategy.

6 CONCLUSION

This paper presented an evolutionary and spatial game theory approach for the problem of self-regulation of exchange processes in MAS, introducing the Game of Self-Regulation of Social Exchange Processes. The agents evolve their social exchange strategies[9], in order to increase their respective exchange strategy-based functions. By this evolution process, the agents achieved the equilibrium of the exchanges, guaranteing the continuation of the interactions and increasing the number of successful exchanges. We considered an incomplete information game, using an evolutionary algorithm for the strategy learning/adpatation process implemented in NetLogo. We showed the emergence of the equilibrium/fairness exchange behavior in the performed simulations, analysing different scenarios.

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