Paper

Partner Selection Using Reputation Information in *n*-player Cooperative Games

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Abstract—To study cooperation evolution in populations, it is common to use games to model the individuals interactions. When these games are *n*-player it might be difficult to assign defection responsibility to any particular individual. In this paper the authors present an agent based model where each agent maintains reputation information of other agents. This information is used for partner selection before each game. Any agent collects information from the successive games it plays and updates a private reputation estimate of its candidate partners. This approach is integrated with an approach of variable sized population where agents are born, interact, reproduce and die, thus presenting a possibility of extinction. The results now obtained, for cooperation evolution in a population, show an improvement over previous models where partner selection did not use any reputation information. Populations are able to survive longer by selecting partners taking merely into account an estimate of others' reputations.

Keywords*—*evolution of cooperation, multi-agent systems, n-player games, partner selection, reputation.

1. Introduction

Modeling of cooperation evolution in populations has frequently used games with cooperative and coordination dilemmas [1], [2]. However real cases frequently do not match model predictions and therefore research tried to explain these results [3]–[9]. A common denominator in the majority of these works is either infinite population or finite but constant size population. Taking into account that these features are unrealistic, a recent line of research [10] has developed a model where populations may fluctuate, and therefore, in extreme cases, may extinguish, which in nature may happen as internal or external influences consequence. In this model the choice of partners is made in groups and does not take into account individual cooperation assessment.

In n-player games used in cooperation models a player usually does not have any information about other players. However it is known that the ability to select partners based on previous interactions knowledge can explain the prevalence of cooperation in many cooperative dilemmas [8]. An approach in which an agent estimates reputation of others from previous interactions [11] has revealed to be efficient towards an extended survival of populations [12].

In this work the authors investigate a combined approach where a population whose individuals can be born, reproduce and die, interact through a n-player game where each agent maintains an estimate other individuals reputation based on its own previous interactions. The model is general enough to encompass any scenario modeled by a n-player game.

2. Related Work

The replicator equation or the Moran process [13] are the most common models to study cooperation. There are a set of assumptions behind the replicator equation [14]. One assumes a considerably large or infinite population. Another assumes a well mixed-population such that everybody plays with everybody else. A similar approach is randomly pairing players. These are unrealistic assumptions and have led to alternative proposals. Among them are structured populations where players are placed in the nodes of some graph and interactions are restricted to links between nodes [15], [16]. In structured populations, agents have the possibility of selecting their partners [5]. Other approaches include finite but constant size population whose dynamics are modeled by a Moran process. Despite not allowing varying population size, they have been used to model scenarios that may cause extinctions such as climate change [17].

In models that allow variable population size most use Agent Based Models (ABM) [18], or are artificial ecosystems [19], [20]. ABM address the difficulties of creating a formal model of a complex system [21]. There are ABMs that analyze the extinctions possibility but they do that in specific contexts such as modeling population growth of endangered species [22], tree mortality [23], impact of logging activities in bird species [24].

McLane *et al.* provide in [25] a review of ABM used in the literature of ecology to address the issues of managing ecosystems. They presented a set of behaviors that individuals can choose in their life cycle: habitat selection, foraging, reproduction, and dispersal. In the papers that they reviewed, some used all the behaviors in the set while others used just one. Such behaviors could constitute the set of actions of some generic game played by animals. Moreover we can roughly divide them in two sets, one where an animal obtains energy (foraging) and a second where an animal spends energy, e.g., habitat selection, reproduction, and dispersal.

Some of these models are characterized by using specific differential equations or operate at higher level than the individual. Often they are specific to their case study and their methods are not directly transferable to another scenario. The Energy Based Evolutionary Algorithm (EnBEA) model [10] with variable population size came up as a solution that can be applied to any scenario modeled by a game. In that model agents are born, they interact with each other, reproduce and die. When that model is applied to a set of cooperative and coordination dilemmas, extinction may occur.

Partner selection is one of the possible explanations for the prevalence of cooperation [26], [27]. This characteristic is also combined with the possibility of refusing an interaction. The selection mechanism is usually dependent on the game: in Prisoner's Dilemma (PD) it depends on the partner defecting or not [8], in trading networks it depends on the trading offer [28]. However, there has been little concern to generalize the mechanism to be applied to any game, which is a problem that this work tackles.

In presented approach a player obtains a reputation representation of other players from results of games he played with them. Reputation is then used by a focal player to choose partners whenever needed. If a player chooses partners with higher reputation he should benefit his outcome in the game. Similar approaches have been followed to study evolution of cooperation [29], [30], sometimes combined with other features such as punishment [31] that favor emergence of cooperation.

Previous work [32] has investigated partner choice based on binary reputation of players, in the PD game. However, a binary reputation is too coarse and does not allow a gradation of reputation. This gradation seems to better correspond to real situations where a binary classification is seldom realistic.

When players assess their peers, this information may be shared with others. This is used in artificial markets where sellers and buyers rate each other [33], [34]. Sabater and Sierra [35] review some models of computational reputation management. They present models where reputation is built from direct interactions or from information given by others. These, as well as other works on player reputation [36], [37] require perfect identification of players.

Kreps and Wilson [38] study the effect of imperfect information about players payoffs in building a reputation about opponents strategies. This is applied to firms competing for a market, in a scenario with a dominant firm and others that, one at a time, may challenge the dominance. Brandts and colleagues [39] made a similar study in loan decision making.

However all these cases use two player games. In [40] a Public Good Provision (PGP) game of three players is used with reputation. A focal player gets perfect knowledge of his neighbors actions in a network of contacts and, for each round, he can choose two partners based on their reputation. The measure of reputation is the number of cooperative actions a player has performed. A similar measure is also used in [41] in a 5-player PGP, also with perfect reputation information.

In the case we are addressing a player does not obtain direct information about individual actions of his partners. We consider that a player only obtains information from his own payoff. This means that he cannot directly identify partners that have not cooperated, nor obtain some kind of signal from them. This is a situation that often occurs in human interaction. In a group of people sometimes is not possible to pinpoint who shirked from contributing. We find that for instance in a n-player snow-drift type game. Suppose a bus that has to be pushed by several individuals. No one knows exactly if a specific individual is cooperating. One can only assess the global outcome in the form of the progress of the bus.

The work in [12] has seemingly been the first to deal with imperfect reputation information in n-player games. This happens for instance in a PGP game when only the player's own payoff is known without access to the individual actions of the players. In such a case, the only situation with perfect information is when all players cooperate. Otherwise each player has an uncertainty about the other $n-1$ players' actions. One or more of them may have defected. That work takes two ways to solve the problem from the point of view of the focal player. One is to have the player using imperfect reputation knowledge to choose his successive partnerships, and the other is to have him gathering individual reputation information from the result of a PGP type game. A private reputation model is used. A player associates to each potential partner a single value that measures his utility. This value is updated from direct interactions with partners, considering all partners in a game as equally responsible for the outcome. The authors classification system is independent of the game being played, which contrasts with others [31] that are game specific.

3. Dynamic Population Model

In this section a formal description of EnBEA is given. It is a population model where agents are born, interact, reproduce and die. Agent interaction is mediated by some game. Interaction is essential because agents acquire or lose energy when playing games and energy is necessary to reproduce. Agents can die because of old age, starvation (lack of energy) and overcrowding.

The games are used as an energy transfer process. This means a redefinition of the payoff function. A game G is a tuple (N, A, E) where N is a set of n players, $A = \{A_1, \ldots, A_n\}$ and each A_i a set of actions for player i, and $E = \{e_1, \ldots, e_n\}$ is a set of energy functions, with $e_i : A_1 \times \ldots \times A_n \to \mathbb{R}$ being the energy obtained by player i given the actions of the n players.

An agent α is characterized by a strategy s which he uses to play game G, an energy level e and an age. We thus have $\alpha = (s, e, a)$. In each iteration t of EnBEA a population of agents, $\mathscr{P} = \{\alpha_1, \ldots\}$ is updated through three phases:

- **play** – in this phase all agents play the game and update their energy. Partners can be randomly selected or agents can choose them;
- **reproduction** – in this phase the agents whose energy is above some threshold produce one offspring by cloning and mutation, and their energy is decremented by some value;
- **death** – in this phase the entire population goes through death events that depend on population size, on agent's age and agent's energy. Age of surviving agents is incremented by one.

In the play phase, the game is used as energy transfer. Regarding the relation between the payoff function and the energy function, the authors have extended the approach followed in [42] and considered the case where the obtained energy is scaled and translated to the interval $[-1, 1]$:

$$e \leftarrow e + \frac{\pi}{\max(\overline{\pi}, |\underline{\pi}|)}, \tag{1}$$

where π represents the payoff obtained by an agent, and $\overline{\pi}$ and $\underline{\pi}$ are the highest and lowest payoffs obtainable in game G.
Scaling allows to compare the evolutionary dynamics of games with different payoff functions, e.g. comparing the number of offspring per iteration or the number of iterations until an extinction occurred. We could remove scaling, if we made energy range equal to payoff range.
With Eq. (1) the possibility of an agent dying through starvation is introduced when the energy drops below zero, thus augmenting the risk of extinction. Instead of zero, we could have used another energy threshold in the decision to remove agents, which would only amount to one more parameter in the model. This case is more realistic as the payoff value reflects gains and costs of an agent. Consider for instance, the costs of providing in the PGP game or of being exploited in the PD game.
When an agent's energy reaches the reproduction threshold e_g, it is decremented by this value, and a new offspring is inserted in the population. Moreover, we have to deal with the possibility of an agent's energy dropping below zero. Similarly to [8] an agent is removed when its energy drops below zero. The energy of newborns could be zero, but this puts pressure on the first played games to obtain positive energy, otherwise infancy mortality may be high. Instead we opt for providing each newborn with e_B units of energy. Therefore, the dynamics of an agent's energy depends on two parameters, namely e_R and e_B.
In order to avoid exponential growth, in each iteration of the algorithm all agents go through death events. The two events are considered: one depends on population size and a second that depends on agent's age. The probability of an agent dying due to overcrowding is:

$$P(\text{death population size}) = \frac{1}{1 + e^{6\frac{K - |\mathscr{P}|}{K}}} \quad , \tag{2}$$

where $|\mathscr{P}|$ is the current population size and K is a parameter called carrying capacity. This probability is a sigmoid function. The exponent was chosen because the logistic curve outside the interval $[-6, 6]$ is approximately either zero or one. In the event of the entire population doubling size, it will not go from a zero probability of dying to certain extinction. This assumes that each agent has at most one offspring per simulation iteration.
The probability of an agent dying because of old age is:

$$P(\text{death agent's age}) = \frac{1}{1 + e^{\frac{L-a}{V}}} \quad , \tag{3}$$

where L is agents' life expectancy and V controls the variance in the age at which agents die through old age.

4. Reputation Model

The reputation model is based on partner selection starting from a random partner selection model that served as base. First the main features of the random model are described and then the reputation mechanism is presented.

4.1. Random Partner Selection

Whenever a focal player needs to play a game, he selects one of the combinations of partners stored in vector **c**. Each combination has a probability of being selected. This probability is stored in vector **p**. The length of these vectors is represented by pool size parameter l. In this model, when a focal player selects his game partners, they cannot refuse playing.
After a player has played the game with partner combination c_k, he compares the utility obtained u with utility threshold u_T. If the utility is higher or equal than the threshold, no changes occur. If the utility is lower than the threshold, the corresponding probability is decreased by factor δ, and the combination is replaced. The following equation represents the probability update policy for the used combination k:

$$p_k^{t+1} = \begin{cases} \delta p_k^t & \text{if} \quad u < u_T \\ p_k^t & \text{if} \quad u \geq u_T \end{cases} . \tag{4}$$

The probabilities of other combinations are updated as follows (to maintain unit sum):

$$p_i^{t+1} = \begin{cases} p_i^t + \dfrac{(1-\delta)p_k^t}{l-1} & \text{if} \quad u < u_T \\ p_i^t & \text{if} \quad u \geq u_T \end{cases} . \tag{5}$$

The used combination is replaced by a new one if the utility is lower than u_T:

$$c_k^{t+1} = \begin{cases} \text{rnd}(\mathscr{C}) & \text{if} \quad u < u_T \\ c_k^t & \text{if} \quad u \geq u_T \end{cases} . \tag{6}$$

If a new combination is to be added, it is previously checked against the ones in the combination vector. If it is identical to any of those, a new one is drawn until it is unique.

The overall behavior of this model is that good combinations remain in the probability vector because they are not replaced and absorb the probabilities of bad combinations.

4.2. Partner Selection with Reputation

In the new model, reputation is used only when a new combination must be drawn in order to replace a combination deemed unacceptable. To represent reputation, a focal player assigns a weight to each possible partner. These weights are stored in vector **w**. When a new combination is drawn, the probability of partner i being selected is proportional to his weight:

$$P(X = i) = \frac{w_i}{\sum_j w_j} . \tag{7}$$

Therefore a weight represents the desire to choose the corresponding player as a partner. It can be considered as his reputation. Higher values mean a partner has a higher reputation and thus should be chosen more often.

We consider that the n-player game does not allow the focal player to identify the partner that has done a particular action. In light of Eq. (7), the model assumes that a player can correctly identify the partners in a combination.

Weights are updated after knowing the result of playing a game with selected combination c_k according to:

$$w_j^{t+1} = w_j^t(1 - p_k^t) + (u - \underline{u})p_k^t , \tag{8}$$

where $j \in c_k$ and $\underline{u}$ is the lowest utility obtainable by the player.

The initial value of the weight vector may depend on the game. An optimistic approach is to define every initial weight to be the utility obtained by a player using a strategy belonging to a Pareto Optimum profile. This is tantamount to consider that all players are cooperative until shown otherwise.

Weight domain is the domain of the utility, but translated by $\underline{u}$ in order to always have positive weights even when the game has negative values. The dynamics of Eq. (8) could be interpreted as assigning to any partner the utility the focal player obtained while playing with him, discounted by probability p_k associated to the combination c_k where the partner is.

Algorithm 1 shows the details the partner selection based on reputation. The parameters of the algorithm are the strategy s used by the player, his set of candidate partners $\mathcal{N}$, the game he is going to play, $\mathcal{G}$, and the parameters of the partner selection model: pool size l, probability update factor δ, utility threshold u_T, and d that is a boolean indicating whether combinations in the vector are all distinct or repetitions are allowed.

Figure 1 lists the parameters of the model and sketches the player architecture.

Algorithm 1. Partner selection with reputation model algorithm

Require: s, $\mathcal{N}$, $\mathcal{G}$, l, δ, u_T, d
  $w^0 \leftarrow f(\mathcal{G})$
  $\mathbf{p}^1 \leftarrow \{p_i^1 : p_i^1 = 1/l \wedge 1 \leq i \leq l\}$
  $\mathbf{c}^1 \leftarrow \{c_i^1 : c_i^1 = \text{rnd}(\mathcal{C}) \wedge 1 \leq i \leq l\}$
  $\mathbf{w}^1 \leftarrow \{w_\alpha^1 : w_\alpha^1 = w^0 \wedge \alpha \in \mathcal{N}\}$
  for $t = 1$ **to** N_I **do**
    select combination of partners from $\mathbf{c}^t$ using $\mathbf{p}^t$
    play game $\mathcal{G}$ and obtain u
    compute $\mathbf{p}^{t+1}$ using Eqs. (4) and (5) with δ, u_T and u
    compute $\mathbf{c}^{t+1}$ using Eq. (6) with $\mathbf{w}^t$, u_T, u and d
    compute $\mathbf{w}^{t+1}$ using Eq. (8)
  end for

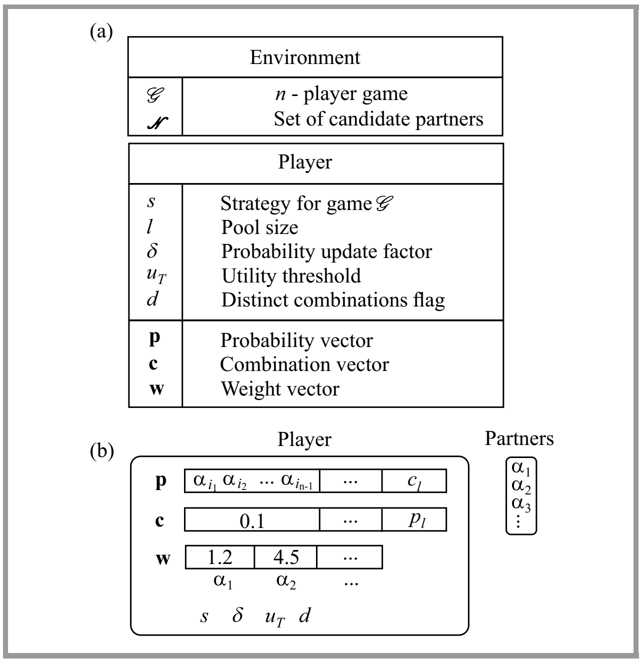

Fig. 1. Player description: (a) the parameters that effect the player, (b) the player architecture.

5. Experimental Analysis

In this section a simulation experiments are described that were conducted to show the capability to support cooperation of the composed model of dynamic populations and reputation based partner selection. The authors selected Public Good Provision (PGP) game, a n-player game to test the model. In this game each iteration involves n players and it does only provide an overall payoff, without identification of whether each player cooperated or defected. This poses the most demanding scenario for an individual reputation maintenance mechanism and that is the reason why such a game was chosen. Besides a description of PGP, this section also identifies the parameter values used for the dynamic population model and the parameter values of the partner selection model using individual reputation.

5.1. Public Good Provision

The authors have performed simulations using the PGP game [43], [44]. This game is commonly studied to anal-

yze cooperative dilemmas. It is considered a generalization of PD to n players. In the PGP game, a player that contributes to the good, incurs a cost c. The good is worth g for each player. The good value was fixed to $g = 1$ and varied the other game parameters n and c. To handle PGP we need to add a single gene, the probability to provide p_p to the agent's chromosome. The mutation operator adds to p_p a random value from a Gaussian distribution with mean zero and standard deviation 0.1. The resulting value is truncated to remain in interval $[0,1]$.
In this game, we have varied the number of players in the game, and the provision cost. Table 1 summarizes the parameters tested in the simulations.

Table 1
Game specific parameters used in the experiments

Parameters used in PGP		
n	Number players	$\{3,4,5,\ldots,8\}$
c	Provision cost	$\{0.1,0.2,\ldots,0.9\}$
p_c	Provision probability	1
$\lvert\mathscr{P}_0\rvert$	Size of initial population	10

5.2. Partner Selection Parameters

The two scenarios have been considered: one with Normal Partner Selection (NPS) – and a second with Reputation based Partner Selection (RPS). The partner selection model adds to the agent's chromosome three more genes. One for the vector size, l, one for payoff threshold π_T and a third for the probability update factor, δ. Whenever the mutation operator is applied to any of these genes, the first gene is perturbed by a discrete Gaussian distribution with mean zero and standard deviation one, while the second and third genes are perturbed by a Gaussian distribution with mean zero and deviation 0.1. In any case, the resulting value is truncated to a valid value. In these simulations, the values of these genes in the initial population were the following: $l = 4$, $\delta = 0.5$ and $\pi_T = 0.5$.

5.3. EnBEA Parameters

In the experiments that were performed a panmictic population was used. Although unrealistic, given that we used a carrying capacity, K, of 100, it is reasonable to assume that all agents can potentially interact with each other. When agents are capable of choosing with whom they will play, networks of agents can be formed. The initial population size was 10.
In this work we are interested in analysing different versions of the games we have used and to measure the occurrence of extinctions. With reproduction energy, e_R, set to 50, an agent that obtains per game the highest payoff, reproduces in less than 50 iterations. Since life expectancy, L, is set to 150, such agent can produce on average three offspring during its lifetime. Offspring were subject to a single-gene mutation with 10% probability. This is an evolutionary model with clonal reproduction subject to mutation.

Table 2
Common parameters used in all scenarios

K	Carrying capacity	100
e_R	Reproduction energy	50
	Energy birth	10
L	Old age	150
	Mutation probability	10%
	Number of iterations	10000
	Number or runs	30

The number of iterations was set to 100000, three orders of magnitude higher than an agent's average lifetime, in order to have a duration enough to observe an extinction or not. In order to obtain statistical results, we performed thirty runs for each parameter combination. Table 2 shows the values of these parameters.

6. Results

For each simulation run we recorded the number of iterations it lasted[1]. This measure is sufficient to assess the impact of weighted partner selection on players survivability. The authors assume that if a simulation reaches the maximum number of iterations (10000) players have successfully gained a foothold in the population.

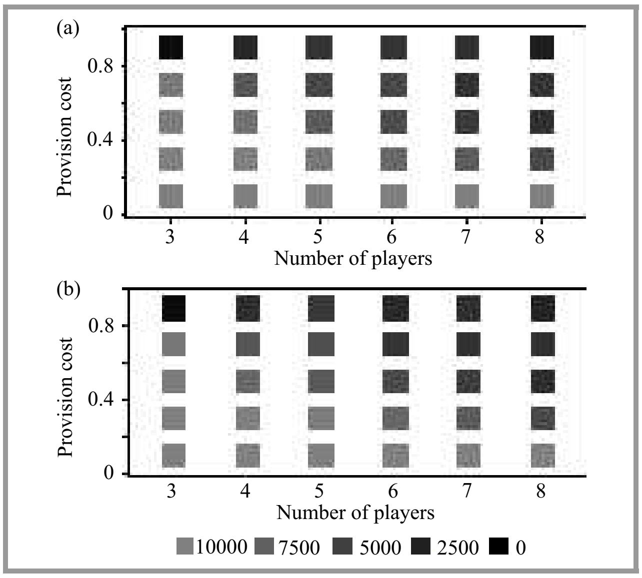

Fig. 2. Average number of iterations in: (a) RPS and (b) NPS scenarios. The lighter is the point, the longer is the corresponding set of simulations.

Figure 2 shows the average number of iterations in both scenarios. Although the fact that parameter values of the partner selection model were set to proper values there are still extinctions compared to previous work [10]. They are more frequent when the game has a higher number of players and higher provision cost. A higher number of players

[1]The simulation was implemented in Mercury, a declarative language, and is available at https://github.com/plsm/EBEA/releases/tag/v2.0.

means a single defector does not impair the payoff of all the other cooperators. It also means that he was more chances of being selected when a new combination is drawn. A high provision cost is beneficial for defectors as there is a higher payoff difference between defectors and cooperators. We also observed simulations where no extinction occurred, namely with low provision cost.

To better analyze the impact of partner selection with reputation, Fig. 3 shows the average number of iterations ratio between RPS and Normal Partner Selection (NPS) scenarios for all parameter combinations of the tested games. In thirteen parameter combinations (triangles pointing upward) the ratio is higher than one, meaning RPS simulations last longer than NPS simulations, while in seven conditions (triangles pointing downward) the ratio is lower than one, meaning NPS simulations last longer.

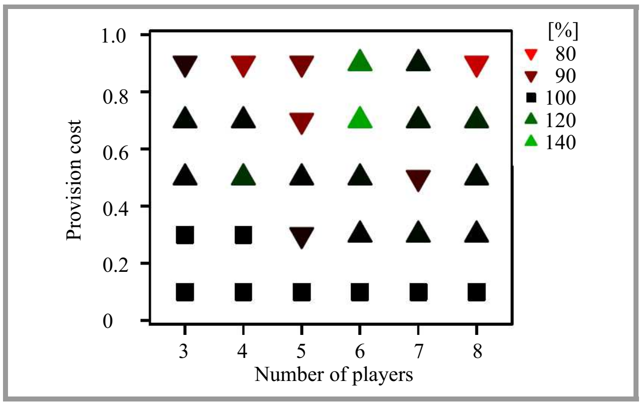

Fig. 3. Average number of iterations ratio between RPS and NPS scenarios: the lighter the point, the longer is the corresponding set of RPS simulations.

The authors have applied a Kolmogorow-Smirnov statistical test between two sets of number of iterations, one for each scenario. The results show that only in one parameter combination ($n = 6 \wedge c = 0.7$) the two sets are from different distributions. In this parameter combination reputation increased the number of iterations. Although there are more parameter combinations with a ratio higher than one, the impact of reputation is not statistical significant (p-value less than 0.1).

Compared to previous work [10], the results reported in this paper are better because agents do not need to evolve the capability to select partners.

7. Conclusions

It is known that simulations with partner selection last longer than simulations with random partners. The improvement is noticeable in PGP although population dynamics are sensitive to initial conditions. If agents in the initial population cannot gain any energy because they are pure exploiters, the population is condemned from the start. However, previous models chose partner groups and not individual partners [10] to create a team of n-players. Also, in that work, the parameter values of the partner selection model of agents in the initial population was set to random selection. Therefore, agents had to evolve the capability of selecting partners. This requires a combination of mutations in the genes that encode partner selection. However, mutation may introduce a defector that exploits existing cooperators thus leading the population to extinction. Here we used as control a model where the initial population starts with the right combination of partner selection parameter values. This means that these results are better than in [10] and this constitutes a more demanding challenge to the new model that uses partner selection based on individual reputation.

In n-player cooperation it is not always possible to identify individual behaviors. This causes an indetermination in case some player fails to cooperate. However even in such a stringent situation it may possible for a focal player to gather information about other players' strategies, by gradually forming their reputations. To model this problem a PGP type game is considered: when all players cooperate the payoff is one, otherwise it is zero. Reputation for each game partner is obtained from the payoff obtained in successive games where he participates. This results in a pessimistic approach with all players from a group of $n-1$ being penalized in case at least one of them defects. When the focal player needs to choose a new partner combination, the probability of choosing a player as partner is proportional to his reputation.

The reputation model is therefore characterized by a weight update policy that does not add any new parameter to the previous partner selection model. It only depends on the payoff obtained by the player, the partner weight, and the probability of selecting the combination where the partner is. This greatly reduces the complexity of the model. The results showed that the reputation model improved the payoff obtained by the focal player. Even when there are not enough acceptable players, the reputation model favored the best $n-1$ partners. As for the parameters of the partner selection algorithm, the best results were observed when the probability update factor was higher and when repetitions were allowed in the combination vector. When all combinations had to be distinct, there could be some bad partner combinations in a larger combination vector.

Results show that this reputation information, for slight it might be, enables higher payoffs for the focal player. Payoff differences between experiments using the reputation model and control experiments decrease with increasing number of partners n. This is consistent with an increased difficulty in assigning responsibility of defection to individual partners. In spite of the more stringent control experiment (with pre-evolved initial parameter values) the reputation model produced slightly better results in terms of number of iterations. Notice that the initial parameter values were chosen based on results of the choice of groups of partners. The reputation model may prove to have even better results with other set of initial values. This is an aspect to investigate further.

In future work, we will also investigate what type of network connections arise with partner selection, how stable a population is, and additional features that delay or avoid extinctions. There are many societal problems such as resource management [45] that can be better analyzed with EnBEA. This can be implemented if a fourth step in EnBEA that given agents' actions is introduced, current game parameters and common parameters such as carrying capacity, returns the set of parameters to be used in the following iteration of EnBEA. One can investigate how agents could be organized, what norms they should follow, which institutions should exist in order to avoid a collapse in the resource base. High game payoffs or carrying capacity values can be interpreted as a stable resource. Lower values can be interpreted as a polluted or depleted resource.

In terms of the reputation model, future work will focus on experimenting different reputation assignments and on other partner selection procedures. The number n of players in a game should influence the modifications to the current reputation. With higher n the modification of an individual reputation should be lower than with smaller n given that the uncertainty about individual responsibility in a negative result is higher. Partner selection taking into account reputation values can me made more or less greedy and this may have significant influence in the results.

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