A Study of the Influence of Trust in Coalition Formation

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Abstract. In multiagent systems, agents may form coalitions in order to cooperatively achieve their goals. Assuming that agents are selfish, or potentially unreliable, they should implement some mechanism to deal with the uncertainty arising from the cooperation. *Trust* is usually chosen as the mechanism for modeling and reasoning about agents' reliability. Hence, this work presents an agent-based simulation model composed of agents who play the spatial prisoner's dilemma game and take into account the notion of trust to form coalitions. Moreover, some experiments are performed and their results suggest that in some cases the notion of trust significantly influences the coalition dynamics.

1 Introduction

The paradigm of multiagent systems (MAS) presents several characteristics suitable for the representation of human societies. Some of these features can be identified in the definition proposed by Wooldridge [13], where MAS consist of a set of autonomous, sometimes selfish agents, situated in a shared environment, which interact among themselves in order to achieve their goals. Among the different kinds of interactions performed, cooperation through coalition formation has been extensively studied through cooperative games, mainly in the field of game theory [1].

According to Griffiths and Luck [6], coalition may be defined as a group of agents in pursuit of a common aim or goal, either to achieve goals that cannot be achieved alone or to maximize net group utility. Therefore, if an agent population is represented as a set A, we may consider that each subset of A is a potential coalition. Furthermore, *coalition formation* is a mechanism that corresponds to the grouping of agents to form a coalition [2].

Nonetheless, cooperation involves risks arising from uncertainties associated with the needed interactions among autonomous and selfish agents. Therefore, some researchers [9,4] propose the use of the notion of *trust* as a mechanism to prevent or reduce the risks associated with such interactions. In this context, trust may be defined as an estimate that an agent has about the actions to be

* Jaime Simão Sichman is partially supported by CNPq and FAPESP/Brazil.

performed by another agent, which directly affect himself and are unknown at the time it needs to decide about which action to perform [5].

Therefore, this work presents a Spatial Prisoner's Dilemma (PD) game [11] that integrates the notions of coalition and trust in order to enable the analysis of the influence that trust exerts in coalition formation. Such analysis is performed by means of a multiagent-based simulation, whose environment consists of a population of selfish agents positioned in a square lattice. Each agent interacts with its neighbors. It can choose either to cooperate or to defect when playing independently. Additionally, it can join or lead a coalition in order to increase its payoff. When it participates in a coalition, the agent always cooperates with agents from its own group and defects with either independent or agents that belong to other groups. The decision to remain or to leave a coalition is largely based on trust information that the agent has about its coalition leader.

The remainder of the article is structured as follows. A brief description of the simulation model, considering the use of the coalition and trust concepts, is presented in Section 2. In Section 3, we summarize some previously obtained simulation results [7], while in Section 4 we propose some new experiments to further investigate the influence of trust in coalition formation. Finally, in Section 5 we present some conclusions and future work.

2 Simulation Model

The simulation model presented in this work is based on a Spatial PD game model presented by Burguillo-Rial [3], which is adapted from a spatial and iterative game approach proposed by Nowak and May [8]. The latter approach states that the interactions among agents consider the spatial structure of the population and they are performed simultaneously by all the agents at each iteration.

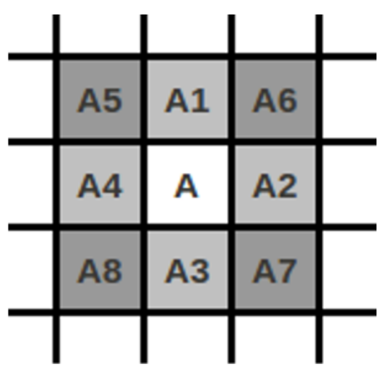

Fig. 1. Agent (A) with two neighborhoods: 4 cells $\{A_1,..,A_4\}$ and 8 cells $\{A_1,..,A_8\}$

Therefore, the spatial structure is represented as a two-dimensional lattice composed of N nodes (Fig. 1). Each node represents a cell, which is controlled by an agent. Each agent A_i can only interact directly with its neighbors, where the neighborhood notion may consider 4 or 8 cells. Additionally, the simultaneous interactions indicate that neither agent knows previously the other agents' actions.

Since the simulation is based on a Spatial PD game, it considers that each agent A_i has two options for acting at each iteration: Cooperate (C) or Defect (D). Playing against the A_j agent, the outcome of this interaction depends on the actions chosen by both agents. The interaction's result of the game with two participants is represented by a classical payoff matrix (Fig. 2) and the parameters values adopted are $T = 5$, $R = 3$, $P = 1$ and $S = 0$.

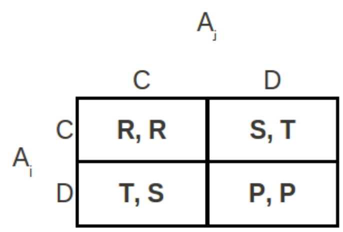

Fig. 2. Payoff matrix for 2-player game

Furthermore, in order to take into account the impact of the coalition strength on the Spatial PD game, the simulation model allows the use of an altered payoff matrix. Such altered matrix payoff was proposed by Burguillo-Rial [3] and it requires the integration of one rule from the game "pay or else" in the simulation model. This rule states that when agents from two different coalitions confront, both suffer some type of loss, but the agent belonging to the smallest coalition is more impacted than the one that belongs to the biggest coalition. This adaptation requires an adjustment in the PD game payoff matrix presented in Figure 2, where Sucker (S) and Punishment (P) payoffs are changed to consider the natural logarithm of the number of agents in the opposing coalition as follows:

$$S_i = S - ln(size(coalition(A_j))) \tag{1}$$

$$S_j = S - ln(size(coalition(A_i))) \tag{2}$$

$$P_i = P - ln(size(coalition(A_j))) \tag{3}$$

$$P_j = P - ln(size(coalition(A_i))) \tag{4}$$

where, S_i and S_j are, respectively, the Sucker payoffs for the agents A_i and A_j, and P_i and P_j are, respectively, the Punishment payoffs for the agents A_i and A_j. Assuming that they belong to different coalitions, therefore, the larger the coalition that the agent belongs, the greater the impact it causes on its opponent. On the other hand, T and R payoffs remain the same as in the classical PD game. As demonstrated in [7], this change in the payoff matrix does not invalidate the premises required for the model to be considered a Spatial PD game.

Moreover, the simulation model adopts a *microscopic* perspective for coalition formation [2]; hence, the agents follow simple rules to make decisions about coalition formation. Coalitions have a two-level organizational structure. One of the coalition's members leads the group and is called the *Coalition Leader*, while the other members are called *Coalition Parts*. Moreover, if an agent does not belong to any coalition, it is called *Independent*. Therefore, agents can play three different roles:

– *Independent*: The agent can either act as a cooperator or a defector with respect to its neighbors, depending on its strategy. After each play, it may join a coalition or remain independent. The agents' strategies are fixed and set at the beginning of each simulation. In this work, the possible strategies are *Tit-for-Tat* (TFT), *Probabilistic Tit-for-Tat* (pTFT) and *Random*;
– *Coalition Part*: The agent cooperates with other neighbors belonging to its coalition and defects with neighbors who are not part of its coalition. It can become an *Independent* agent if its trust value on its leader drops below a threshold value;
– *Coalition Leader*: The leader acts like its parts; however, the leader cannot decide to become independent at anytime: he can take this decision only when there is no other *Coalition Part* agents in the coalition that he leads. It also imposes a tax percentage to the payoff of the *Coalition Part* agents.

The simulation model also adopts an *individual trust* approach [10] for trust modeling. Hence, each agent implements a simple trust model to evaluate its *Coalition Leader*'s trust. In such a trust model, trust value is represented by a single integer number between 0 and 100, where values close to 0 represent a low confidence, and values close to 100 represent a high confidence on the *Coalition Leader*. As the agents progress through the game, they update the value of the leader's trust, based on their past experiences. Thus, by using such information, an agent can decide to remain in or to leave the coalition.

Since agents have group rationality, they join a coalition only if they can benefit at least as much as the sum of their personal benefits outside of the coalition [2]. However, in order to leave a coalition, their decision is based on its trust on its *Coalition Leader*, whose value is directly related to the payoff received from the latter.

When an agent belongs to a coalition, it cooperates with agents in its coalition and defect with all others. During each iteration, the leader receives the payoff of all agents who belong to its coalition, subtracts the tax percentage and evenly redistributes the remaining payoff among all the *Coalition Part* agents. Since each agent may consider to use or not trust to make decisions related to coalition formation, two algorithms Algorithm 1 and Algorithm 2 are proposed. In those algorithms, A_m and A_k are respectively the agents who received the highest/lowest payoff among the neighboring agents of A_i.

Algorithm 1 Coalition Formation Algorithm With Trust

```
if HasLeader(A_i) then
    if Payoff(A_i) ≥ Payoff(A_m) then
        trustLeader = Min(100, (trustLeader + deltaTrust))
    else
        trustLeader = Max(0, (trustLeader - deltaTrust))
        if trustLeader < trustThreshold then
            Independence(A_i)
        end if
    end if
else
    if Payoff(A_i) ≤ Payoff(A_k) then
        JoinCoalition(A_m)
    end if
end if
```

In Algorithm 1, agent A_i is setup to use trust. Let us consider that it is a *Coalition Part* agent. The agent first checks if its payoff is greater than or equal to A_m's payoff. If so, it increases its trust on the leader; otherwise, it decreases its trust on the leader. Then, it checks if its trust value dropped below a specified threshold. If so, it becomes independent from the coalition. On the other hand, when the agent A_i is *Independent*, it checks whether its payoff is less than or equal to A_k's payoff. If so, it decides to join the A_m's coalition, and otherwise, it remains *Independent*.

Algorithm 2 Coalition Formation Algorithm Without Trust

```
if HasLeader(A_i) then
    if Payoff(A_i) < (Payoff(A_m) / 2) then
        Independence(A_i)
    end if
else
    if Payoff(A_i) ≤ Payoff(A_k) then
        JoinCoalition(A_m)
    end if
end if
```

On the other hand, in Algorithm 2 the agent does not consider trust. The only difference from the previous algorithm is that its decision to leave the coalition is not based on the trust threshold, leaving the coalition if its payoff is less than half of A_m's payoff.

Readers interested in further details about the simulation model[1] and its dynamics are pointed to [7].

[1] The model is available at http://www.openabm.org/model/2620/version/1.

3 Previous Results

In our previous work [7], we proposed some preliminary experiments to analyze whether the fact of taking into account the notion of trust would affect the coalition formation. The experiments proposed can be classified according to two dimensions as depicted in Figure 3:

– *Payoff Matrix* dimension which indicates the payoff matrix applied (*Standard* or *Altered*)
– *Trust* dimension which indicates whether the notion of trust was or not used by the agents in coalition formation

	No TRUST	**TRUST**
Standard Payoff Matrix	**1**	**2**
Altered Payoff Matrix	**3**	**4**

Fig. 3. Classification of the experiments in Payoff and Trust dimensions

Analyzing the results of these experiments, we noticed that the notion of trust had an impact on coalition formation only when applying the *Altered* PD game payoff matrix (Quadrants 3 and 4), but not when applying the *Standard* PD game payoff matrix (Quadrants 1 and 2). Therefore, we concluded that *Trust* is not much relevant for coalition formation if belonging to a coalition does not bring any other benefits or penalties than playing independently.

Therefore, the motivation of performing these new experiments was to explore further changes in the macroscopic patterns of coalition formation, basically due to variations in those parameters related to the notion of trust in order to corroborate with the previous results. Thus, the focus of this work is on experiments in the Quadrant 2, represented in grey in Figure 3.

4 Experiments

In this section, we investigate the effects of trust in coalition formation by performing simulations using the model presented in Section 2.

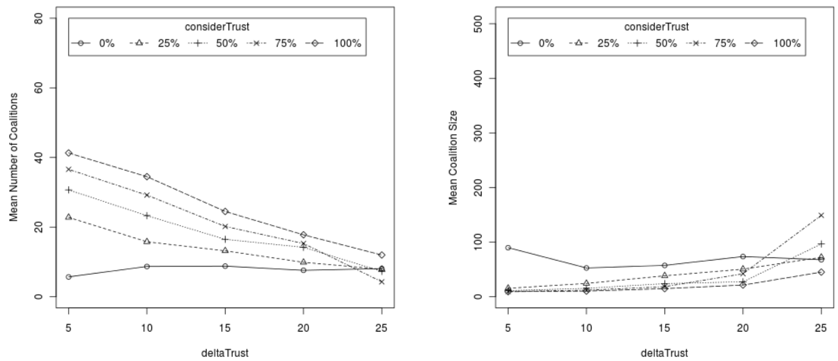

Fig. 4. Graph of number and size of coalitions [$tax = 25\%$ and $trustThreshold = 25$]

All simulations were performed using NetLogo 4.1.2 [12] running on a PC (Intel i5 2.53 GHz with 4 GB of memory) with Linux Ubuntu 10.10.

At the beginning of the simulations, each agent randomly selected a number between 0 and 100, which was compared to the value of a parameter (*considerTrust*) that represented the probability of taking the notion of trust into account to form coalitions. If this random number was smaller than this parameter value, then the agent selected the Algorithm 1 (with trust), otherwise the agent selected the Algorithm 2 (without trust). Furthermore, each agent's role was setup to *Independent*, and its strategy was randomly chosen among the three available strategies (TFT, pTFT and Random). Thus, as long as the agent remained *Independent*, this strategy was used during the whole simulation.

Some of the parameters were set with a fixed value for all the simulations: the lattice size was set to 21 x 21 = 441 positions; the number of iterations was set equal to 1000 (*rounds*); all agents use the *Standard* PD game payoff matrix (*coalitionStrength* disabled); the possible strategies that agents could use were pTFT, TFT, and Random (*strategy*), which were randomly chosen at the simulation initialization; and the neighborhood was set to 8 (*numNeighbors*). These parameters were arbitrarily chosen, but, since they were fixed for all simulations, we assumed that their selection did not interfere in the results and consequently in the analysis. The parameter *rounds* was set to 1000 because we observed that most of the experiments stabilized before this iteration.

The simulation scenarios were setup combining the following parameters: the tax percentage imposed by the leader ($tax = \{25, 50, 75\}$); the probability agents had to use trust in order to remain or to leave a coalition ($considerTrust = \{0, 25, 50, 75, 100\}$); the variation of trust ($deltaTrust = \{5, 10, 15, 20, 25\}$); and the trust threshold ($trustThreshold = \{25, 50, 75\}$). Each simulation scenario was executed 10 times, therefore, we performed 2250 simulation executions.

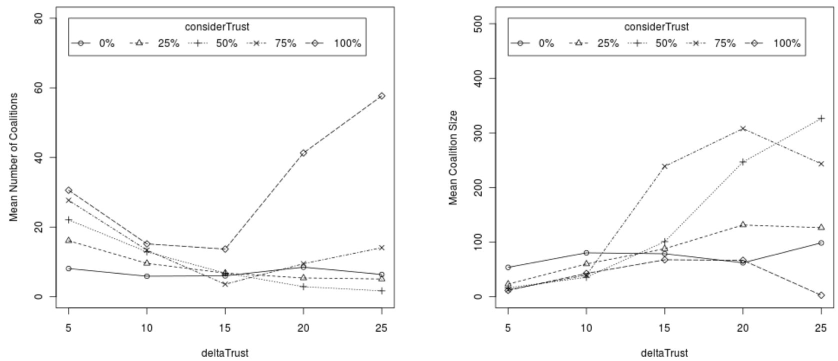

Fig. 5. Graph of number and size of coalitions [$tax = 25\%$ and $trustThreshold = 50$]

The simulation model allowed the monitoring of various measures of macroscopic patterns of coalition formation. In this work, we concentrated specifically on three of them: number of coalitions, coalition size and number of *Independent* agents. These measures gave us an indication of the macroscopic pattern behaviors, in particular, we could identify that when the *tax* was set to 50% or 75% the macroscopic behavior was similar for all the combinations of *deltaTrust* and *considerTrust* values. In these scenarios, the system became very dynamic, where dynamic means rapid formation and dissolution of small coalitions, with a great number of independent agents. Moreover, we observed that increasing the *deltaTrust* and *considerTrust* values also increased the number of *Independent* agents.

However, when the *tax* was set to 25%, the macroscopic behavior varied depending on the combination of *deltaTrust* and *considerTrust* values, as depicted on the Figures 4, 5 and 6. In Figure 4 and 5, when the *trustThreshold* was respectively set to 25 and 50, we observed that as *deltaTrust* increased, the system became *more stable*. This stability was identified by the *decreasing number of coalitions* and *their increasing medium size*, except when $considerTrust = 100\%$ and $trustThreshold = 50$.

In Figure 6, when the *trustThreshold* was set to 75, we observed that as the *deltaTrust* increased the system became *less stable* for *considerTrust* values greater than 75%. While considering other *considerTrust* values, the system remained constant, however, with a *reduced number of coalitions* and *great number of independent agents*.

5 Conclusions and Future Work

This paper briefly presents a simulation model that adopts a microscopic approach to simulate a Spatial PD game, integrating both the concepts of coali-

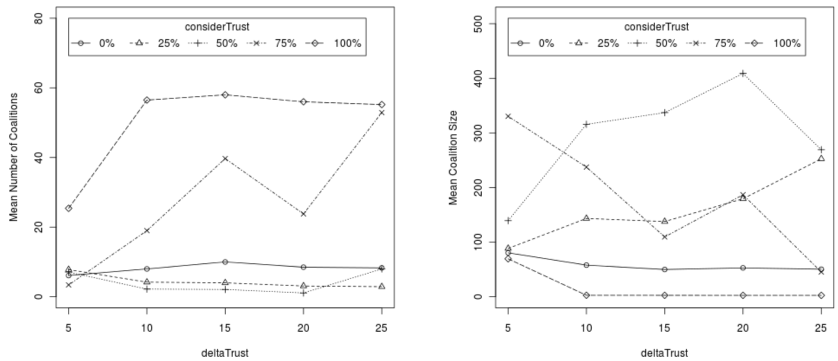

Fig. 6. Graph of number and size of coalitions [$tax = 25\%$ and $trustThreshold = 75$]

tion formation and trust. In this game, players can either act independently or form coalitions; additionally, coalition formation can be influenced by the notion of trust. We conducted some experiments to identify the influence of trust in coalition formation. We identified that high *tax* values make the system more dynamic and trust is not much relevant for coalition formation, corroborating with the analysis made in [7]. On the other hand, when considering low *tax* values, the system behavior becomes more dependent on trust, since the system becomes more unstable as we increase the percentage of agents that consider trust and the trust threshold. As future work, we intend to better specify the notion of coalition stability.

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