Emerging Cooperation on Complex Networks

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ABSTRACT

The dynamic formation of coalitions is a well-known area of interest in multi-agent systems (MAS). Coalitions can help self-interested agents to successfully cooperate and coordinate in a mutually beneficial manner. Moreover, the organization provided by coalitions is particularly helpful for large-scale MAS. In this paper we present a distributed approach for coalition emergence in large-scale MAS. In particular, we focus on MAS with agents interacting over complex networks since they provide a realistic model of the nowadays interconnected world (e.g. social networks). Our experiments show the effectiveness of our coalition emergence approach in achieving full cooperation over different complex networks. Furthermore, they provide a clear picture of the strong influence the topology has on coalition emergence.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent Systems*

General Terms

Algorithms,Experimentation

Keywords

cooperation, coalition emergence, consensus, MAS

1. INTRODUCTION

Achieving cooperation and coordination in multi-agent systems is a challenging issue [10]. These becomes even more difficult to accomplish when dealing with *self-interested* agents. Cooperation among self-interested agents is often hindered by *social dilemmas* [9]. In these dilemmas, agents must decide between a (short-term) individual benefit or a (long-term) group benefit. Individual decisions (self-interested), besides providing only momentary benefits, are detrimental if many agents take them (e.g. if many individuals try to download the same file at the same time, their download speed suffers greatly). Instead, group decisions (social) can result in a mutually beneficial cooperation that holds over time [17]. In MAS, examples of social dilemmas can be often observed in frequency spectrum assignation, load balancing, packet/message congestion, bandwidth allocation, etc. Therefore, mechanisms that promote the emergence and maintenance of cooperation for self-interested agents is an area of interest [7].

The emergence of cooperation is often studied in the context of the Prisoner's Dilemma (PD) theoretical framework [2]. This has been specially useful for understanding the role of local interactions and the maintenance of cooperation [16, 13, 11]. Moreover, these studies have been successfully applied to existing applications (e.g. Peer-to-Peer (P2P) systems [8]). Nonetheless, in P2P and many other complex systems, the problems relating to social dilemmas still exist.

To prevent social dilemmas and promote cooperation, Axelrod proposed a tribute/tax model [3]. According to this model, cooperation is achieved when agents form *coalitions* around some emerging *leaders*. To maintain their coalitions, leaders charge their agents some tribute/tax. In other words, leaders extort other agents with some pay in favor of a benefit (e.g. guaranteed cooperation, protection against cheaters). This is a clear example of the known tradeoff between the benefits *vs.* the costs of collaboration (e.g. taxes) [18].

Axelrod's model has been successfully adopted to help agents, on grid topologies, cooperate when using a spatial version on the PD [5]. However, whether cooperation is still possible on actual-world topologies via a tribute/tax model, such as the one described by Axelrod [3], remains *unexplored*. Complex networks provide a more realistic model of the topological features found in many nature, social and technological networks (e.g. social networks, the Internet, ecological populations) [1, 19]. Furthermore, it is known that they can influence emergence [15].

The main contribution of this paper is the design of a mechanism to emerge and sustain *full* and *profitable* cooperation, via a *single super-coalition*, but with a low collaboration cost (tax). Specially, since we found that: a) the coalition strategies employed by [5] cannot accomplish full cooperation on complex network topologies; and b) that the notion of tribute (having leader agents setting taxes) is unfair for the population as a whole. Therefore, our proposed approach contributes with: i) a set of coalition strategies that promote a profitable cooperation on complex networks; and ii) a consensus mechanism that allows coalition members themselves (instead of leaders) to reach a convention over the *fair* price to pay to be part of a coalition. Thus, unlike Axelrod's model, agents in our approach are no longer subject to leader extortion. Overall, this results in an ap-

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proach fair and profitable for all agents.

Moreover, we show that our approach has a high degree of *resilience* against the leader's failure. This is important, because if a leader fails, its whole coalition collapses, halting the cooperative behavior (i.e. leaders induce a single-point of failure). However, in our approach after the leader fails, agents promptly emerge a new coalition.

The paper is organized as follows. Section 2 briefly describes the base model and presents its evaluation on different complex networks. Next, in section 3 we propose and evaluate both a new set of coalition strategies and our consensus mechanism. Finally, in section 4 we draw some conclusions.

2. A BASE COALITION FRAMEWORK

The purpose of this section is twofold. Firstly, section 2.1 introduces the base mechanism for coalition emergence that we subsequently extend (in section 3) to support cooperation over complex networks. Secondly, in section 2.2 we empirically analyze the performance of the base mechanism over complex networks.

2.1 The Base Approach

In this section we summarize the model for coalition formation that we extend in this paper. The model is thoroughly described in [5], and it is based on Axelrod's model for the emergence of political actors described in [3]. The main motivation of the Axelrod's model in [3] is to promote cooperation by increasing the organization level of a multi-agent system. This is accomplished through the emergence of some leading agents that command coalitions of previously independent agents. Each agent within a coalition cooperates with its leader agent. Moreover, the leader also imposes the strategic behavior to follow against members and non-members of the coalition. Consequently, notice that the emergence of a single coalition guarantees full cooperation between all agents.

The model in [5] considers an agent population using a grid as its interaction topology. The interaction between agents is modeled as an n-person game, i.e. n agents interacting simultaneously, where each game is a spatial version of the Iterated Prisoner's Dilemma (IPD) [13] that takes into account each agent's number of neighbors. Every agent must decide whether to behave as a defector or cooperator during each round of the game, and they are payed according to the payoff matrix depicted in table 1. Therefore, in an attempt to maximize their individual payoffs, agents must also decide whether to join or leave a coalition, or switch to another one. To summarize, the model is composed of: (1) a role model describing the roles each agent may take on (independent, coalition member, and leader); (2) a game-based interaction model describing how agents interact (spatial IPD); (3) a collection of interaction strategies for the roles that agents play; and (4) a collection of *coalition strategies* for the roles that agents play.

First, the role model considers that each agent can play one out of three mutually exclusive roles:

- An *independent* agent decides its own interaction strategy (whether to cooperate or defect) during each game. It decides its next action using a probabilistic Tit-for-Tat (pTFT) strategy [5]. Unlike classical TFT [4], a pTFT strategy stochastically imitates the action played by the majority of an agent's neighbors in a previous round. Additionally, it has coalition strategies to decide whether to join or not a coalition.

- A *coalition member* agent leaves the decisions regarding its interaction strategy to its coalition leader. However, it still has coalition strategies to decide whether to leave the coalition (to either switch to a better one or in favor of independence) or stay in it. Moreover, a coalition member must pay some tax to its leader for the right to remain in the coalition. This tax serves as a guarantee for cooperation within the coalition.

- A *coalition leader* agent decides the interaction strategy for the whole coalition. Leaders impose that all the agents within a coalition cooperate between them, but defect when interacting with agents outside the coalition. A leader cannot disband its coalition. However, it must decide the taxes that its coalition members must pay to remain in the coalition. Notice that by applying a tax percentage to its coalition members, a leader increases its own income. A leader's income depends on: the amount of tax, the number of agents in the coalition, and the income of coalition members. Therefore, although choosing high taxes may lead to more short-term revenues, it may also lead to bankruptcy of coalition members, and hence to the collapse of the coalition (as observed in [3]).

		Agent j C	Agent j D
Agent i	C	(3,3)	(0,5)
	D	(5,0)	(1,1)

Table 1: Prisoner's Dilemma Payoff Matrix

Now we turn our attention to the actual coalition strategies employed by agents to decide whether to join, leave, or switch coalitions. These decisions mainly depend on the agents' payoffs when compared with their neighbors, and on their commitments. The notion of *commitment*, introduced in [3], reinforces cooperation between agents with previous cooperative interactions. In what follows, we abstract the coalition strategies presented in [5] as a collection of qualitative, role-based strategies:

Independent agent decision-making

1. *Join coalition (worst agents).* **If** my payoff is the worst in my neighborhood **then** join my best (payoff-wise) neighbor's coalition (request to form one if needed).

2. *Join coalition (moderate agents).* **If** my payoff is average in my neighborhood **and** I am committed to my best neighbor **then** join its coalition (request to form one if needed).

Coalition member decision-making

3. *Leave coalition (isolated agents).* **If** I am isolated (connection wise) from my coalition **then** leave it.

4. *Strengthen coalition (satisfied agents).* **If** my payoff is good **then** increase my commitment with my leader.

5. *Coalition switch (worst agents).* **If** my payoff is the worst in my neighborhood **and** the agent with the best payoff in my neighborhood is not my leader **then** switch to the best agent coalition.

6. *Coalition switch (unsatisfied agents).* **If** the agent with the best payoff in my neighborhood is not my leader **and** I have some commitment with this best agent **then** switch to its coalition.

7. *Leave coalition (unsatisfied agents).* **If** my commitment to the leader is low **and** the agent with the best payoff in my neighborhood is not my leader **and** this best agent is independent **then** leave my coalition.

The strategies above allow agents to decide how to behave with respect to coalitions. Firstly, only independent agents that are not obtaining good payoffs consider joining a coalition (strategies 1 and 2). Secondly, an agent obtaining good payoffs in its coalition, strengthens its commitment to the leader (strategy 4). Otherwise, an agent that performs poorly switches from its current coalition (strategy 5), whereas an agent that does not perform poorly but is unhappy with its leader may also either switch coalition (strategy 6) or simply leave the coalition (strategy 7) looking for potentially better coalitions.

Moreover, the model allows some exploration regarding interaction and coalition strategies by the introduction of a *mutation* probability. Mutation may randomly change either the action that independent agents choose to play during interactions, the decisions of agents regarding whether to leave a coalition or not, and the taxes charged by leaders. Therefore, mutation adds exploration to the strategic behavior of independent agents, coalition members, and leaders.

2.2 Coalition Formation over Complex Networks

As stated above, the approach proposed in [5] was successful in helping agents achieve full cooperation (or close to it) on grids. However, grid or grid-like topologies may not model the connectivity/topology that a MAS application may find in a more realistic environment (e.g. P2P, social networks). It has been argued that complex networks provide a more realistic model of the topological features found in many nature, social and technological networks [1, 14] (i.e. computer networks, social networks). Therefore, complex networks provide actual-world topologies where we can evaluate if the coalition formation results exhibited on the grid topology hold. Hence, in this section we aim at evaluating this coalition formation approach (hereafter referred to as the base approach) on actual-world topologies.

To that end, we ran a series of simulations of the base approach over different complex networks. The networks that we employed along with the results are described and discussed in the following subsections.

2.2.1 Network Topologies

This paper's experiments focus on small-world and scale-free networks since these type of networks are the ones that best model the most common networks appearing in societies and nature.

Small-world: These networks present the small-world phenomenon, in which nodes have small neighborhoods, and yet it is possible to reach any other node in a small number of hops. This type of networks are *highly-clustered* (i.e. have a high clustering coefficient). Formally, we note them as $W_V^{k,p}$, where V is the number of nodes, k the average connectivity, i.e., the average size of the node's neighborhood, and p the re-wiring probability. We used the Watts & Strogatz model [19] to generate these networks.

Scale-free: These networks are characterized by having a few nodes acting as highly-connected hubs, while the rest of them have a low connectivity degree. Scale-free networks are *low-clustered* networks. Formally we note them as $S_V^{k,-\gamma}$, where V is the number of nodes and its degree distribution is given by $P(k) \sim k^{-\gamma}$, i.e. the probability $P(k)$ that a node in the network connects with k other nodes is roughly proportional to $k^{-\gamma}$. We used the Barabasi-Albert algorithm [1] to generate these networks.

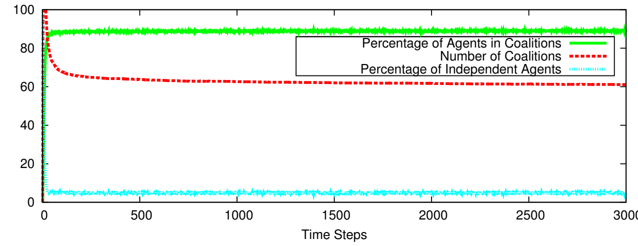

Figure 1: Coalitions in small-world topologies

2.2.2 Experimental Settings

The settings described in this section are also those that will be employed in the rest of this paper (unless otherwise indicated). Each *experiment* consisted of 50 discrete event simulations, each one running up to 20000 time steps (ticks). Each simulation ran with 1000 agents over either a small-world or scale-free underlying topology. Moreover, all the metrics of the simulations were aggregated using the inter-quartile mean (IQM). The experiments used a mutation probability of 0.05 (the same reported in [5]).

In all simulations, interaction topologies were generated by setting the following parameters: $W_{1000}^{10,0.1}$ in small-world networks and $S_{1000}^{10,-3}$ in scale-free networks. The clustering coefficients of the topologies are high (0.492) and low (0.056) respectively. Notice that a new interaction topology is generated per simulation.

2.2.3 Experimental Results

The purpose of first experiments was to determine whether or not the base approach is influenced by the underlying topology. To analyze the results we observed : i) the number of coalitions and independent agents (the closer to a single super-coalition, the higher the cooperation); ii) each agents' payoff with respect to its maximum payoff (the cooperation reward $\times$ the number of neighbors) and taxes; and iii) the topology of the leaders' neighborhoods. In general, the experiments showed that the behavior of the base coalition formation algorithm is strongly dependent on the network topology as we discuss next.

Small-World. Firstly, we observed that in MAS with a small-world connectivity (see figure 1), multiple coalitions emerged (~ 60). This fragmented population is quite a contrast with respect to the grid results, where a single coalition emerged given enough time. Moreover, figure 1 also shows that, at any given time step, around 5% of the population

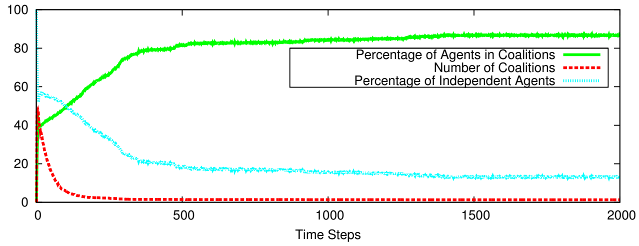

Figure 2: Coalitions in scale-free.

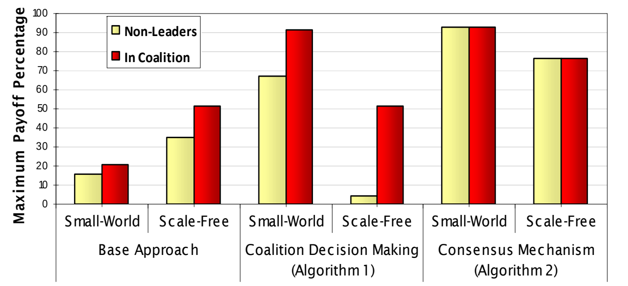

Figure 3: Non-leader (in coalition+independent) agents average payoff.

remains independent. However, the ceaseless spikes exhibited by the plots of both agents in coalitions and independent agents, indicate that agents are continuously leaving and joining coalitions. In other words, coalitions are rather *unstable* because their members continuously change.

With respect to the payoffs, figure 3 shows that the average payoff of an agent in a coalition is significantly low ($\sim$ 20 % of the maximum). Specially when compared with the $\sim$ 99% (of the maximum) obtained in the grid simulations (in [5]). The reasons behind this lower payoff are two-fold: 1) a *fragmented population*; and 2) *very high taxes* imposed by leaders. The former means that as a result of multiple coalitions and independent agents, it is very likely for agents in a coalition to interact (play) with agents outside their coalition (for which their strategy is an automatic defect). The latter occurs because leaders are not pushed to decrease their taxes. In particular, leaders charge their coalition members a $\sim$ 44% of their total payoffs. That fact that agents settle on paying such high taxes greatly differs from the results obtained on grids, where low tax values ($<$ 1% of the total payoff) were reached.

Scale-free. The results over scale-free topologies (depicted in figure 2) show that agents promptly gravitate towards a single leader, thus forming a single super-coalition. However, not all agents join the coalition ($\sim$ 18% of the population, namely $\sim$ 180 agents, remain independent). Moreover, figure 2 exhibits the same kind of instability exhibited by the small-world case (illustrated by the ceaseless spikes).

Interestingly, agents on this topology receive a higher payoff ($\sim$ 50% of the maximum payoff) than on small-world topologies, but still far from the 99% obtained in grids . This occurs because a highly populated single coalition amounts to a very high level of cooperation (i.e. $\sim$ 80% of the agents cooperate with each other). Nonetheless, once again, like in the small-world case, the agents in the coalition also pay very high taxes ($\sim$ 44% of their total payoff).

Moreover, an in-depth analysis of the simulations showed that the agents that became leaders had an interesting characteristic in common. They tend to be the agents with higher connectivity (i.e. they have more neighbors). Hence, the hubs (in particular the highly connected ones, although not necessarily the most connected ones) usually emerge as leaders. Consequently, this is also the reason why a single leader can emerge, since the considerable high number of neighbors that hub agents have with respect to the rest of agents ($\sim$20 vs. $\sim$150) puts them in an excellent influence position. Moreover, the relatively low number of hub agents means that only a few agents compete between themselves to become a leader, thus it is easier for one of them to dominate others.

In contrast, the neighborhoods under small-world topologies are very similar [1] (on average each agent has $\sim$ 10 neighbors) and thus all agents have more or less the same level of influence. Hence, this explains why multiple coalitions coexist (agents start with similar levels of influence).

Summary. Overall, the main drawbacks of the base model are: its sensitivity towards the topology and the coalitions' instability. The first one may be solved by analyzing and revising the base decision making logic (i.e. the coalition strategies), whereas the second issue is harder. The instability exhibited by coalitions mainly occurs because the high mutation (0.05) prompts the agents to *leave* their coalitions (as stated above). However, for large coalitions to appear, high mutation is necessary on both grid (as argued in [5]) and complex network topologies. In other words, mutation is both detrimental and crucial for the coalition formation process. Hence, adjusting mutation is challenging when we want to minimize the instability without affecting coalition emergence.

In the next section we focus on improving cooperation mainly by solving or minimizing the above-mentioned drawbacks.

3. IMPROVING COOPERATION

The aim of this section is to study how to maximize cooperation amongst agents (and consequently improving their payoffs). To that end, the base approach needs to be revised and extended to address the drawbacks identified in the previous section.

Specifically, along this section we focus on: a) achieving full cooperation by emerging a single super-coalition (avoiding a fragmented population); b) sustaining the single coalition through time by minimizing coalition instability; and c) lowering the taxes needed to maintain the coalition. Moreover, all of these needs to occur regardless of the underlying topology. However, notice that although a single coalition promotes cooperation and is beneficial for the agents' payoffs, a single leader becomes a potential single-point of failure, making the MAS vulnerable. Therefore, we also commit to an additional objective: d) the promptly re-emergence of a coalition if the leader fails.

3.1 Topology Influence

The experimental results in section 2.2 showed that the base coalition formation approach is considerably sensitive to the MAS underlying topology. In particular, we observed that the topology influences the structure of coalitions (frag-

[1]because of the small-world phenomenon, see [19]

mented population vs. single coalition). However, the topology also influences other aspects of emergence, i.e. the emergence time. Hence, the purpose of this subsection is to perform a sensitivity analysis of the decision making process (described in subsection 2.1) with respect to the topology.

3.1.1 Influence on Coalition Structures

The most noticeable topological effect observed during the previous experiments was the fragmented population. Specifically, in small-world topologies agents form multiple, different coalitions, which are detrimental to their total payoffs. Therefore, in what follows we aim to promote the emergence of a single coalition.

To understand why multiple coalitions emerged instead of a single one, we must first explain how we expected the base approach to behave. Initially, regardless of the topology, agents organize in small coalitions. Then, agents were expected to leave their coalitions in favor of independence or better coalitions if their payoffs were not sufficient. In other words, by continuously joining and leaving coalitions, agents were expected to incrementally move towards larger coalitions (under the principle that the larger the coalition the higher the payoff) until only a single one remained. However, as the experiments demonstrated in subsection 2.2.3, this behavior does not occur on small-world topologies. Hence, the join and/or leave coalition strategies do not behave as needed.

We determined that the shortcoming stems from *join coalition* strategies instead of leave coalition strategies. Our reasoning is that because of high mutation some agents will always leave their coalitions, thus the fault occurs when they (re-)join them. That is to say, in small-world topologies the join strategies are not moving the agents towards a larger coalition, and instead they keep the population fragmented. Specifically, this occurs because the combination of the small-world's inherent high clustering, the *commitment* notion, and *join coalition strategy 2*, prompt each agent to rejoin the coalition they just left (i.e. most agents never truly leave their coalitions).

We re-ran the experiments to verify if the *join coalition strategy* 2 truly halts the emergence of a single coalition. As expected, we confirmed that without this strategy, agents on small-world topologies are capable of emerging a single super-coalition. Moreover, interestingly enough we found that agents in the single coalition have the additional advantage of paying a significantly *low* tax (∼5% of the agent's total payoff instead of ∼44%). The reason behind such low taxes is very reasonable. The fact that every agent can potentially become a leader (as discussed in section 2.2.3) drives a fierce competition between leaders to charge lower taxes (akin to a price war). Overall, low taxes translate onto higher payoffs for coalition agents (∼90 % of the maximum), which is our main objective. Nonetheless, the instability of coalitions is still present and is accountable in lower average payoff obtained by the non-leader agents when compared to the coalition agents (see figure 3).

Nevertheless, the removal of join coalition strategy 2 is detrimental to scale-free topologies. Because of the highly connected hubs in scale-free networks, a single coalition promptly emerges. However, the low clustering of scale-free networks causes agents that recently became independent to remain independent for longer periods of time. This considerably increases the coalition's instability (around one third of the agents are independent at any given point in time). Basically, without a strategy to force agents into a coalition (such as join coalition strategy 2), the number of agents leaving a coalition is higher than the number of agents joining one. In other words, scale-free suffers the full-blown effect of mutation.

To summarize, we reaffirmed the fact that the effect of the coalition decision making process varies depending on the network topology. However, since agents are not capable of identifying the underlying topology where they interact, creating specific strategies for each topology is unrealistic. Nonetheless, when join strategy 2 is removed, coalition emergence is relatively similar in both small-world and scale-free, since only single coalition emerges. This is important because now only *one drawback* remains for both topologies: *instability* (although to a much higher degree in scale-free). Therefore, the remaining objective is to minimize instability, which is the focus of subsection 3.2.

3.1.2 Influence on Emergence Time

In the previous subsection we determined that a single coalition can emerge regardless of the topology. However, we did not mention that the time required for this single coalition emergence varies depending on the topology. In particular, we observed that agents in small-world require a longer time to group up unto a single coalition (4000 time steps) with respect to the agents on scale-free ($<$ 500 time steps). This time disparity is once again a product of the strong influence that hub agents have over the rest of agents. Thus, in this section we aim to speed-up the coalition emergence process on both topologies.

In the base approach, the switch and leave coalition strategies (3,5,6, and 7) are expected to improve coalition emergence time, since they prompt agents to leave their coalitions in search for better ones. However, the leave strategies targeting unsatisfied agents (6 and 7) are hardly ever employed. Therefore, we propose to replace them with the by far more aggressive *disband coalition* strategy. With this strategy, leaders of unprofitable coalitions may disband their coalitions and free multiple unsatisfied agents in just a single time step. This can be regarded as the dual of strategies 6 and 7, since instead of each agent leaving its leader, the leader leaves all its agents.

8. *Disband coalition (unsatisfied leader).* **If** I am a leader and I am not satisfied with my payoff **then** disband my coalition.

Algorithm 1, stands for the resulting coalition decision making process. Notice that after removing the join and leave strategies (strategies 2,6, and 7), none of the remaining strategies employ the notion of commitment employed in Axelrod's tribute model [3]. Thus, the strengthen coalition strategy (strategy 4) was also removed. That is to say, commitment between agents is not actually needed for coalition emergence. We re-ran the simulations to verify the speed-up provided by algorithm 1.

The results showed that by employing the disband strategy a single coalition emerges ∼ 12.5 % faster (than when employing strategies 6 and 7) in a small-world topology. Moreover, it speeds up the emergence on scale-free by ∼ 50%.

Overall, we have simplified the agents' coalition decision making algorithm. Therefore, we can now turn our attention to our remaining drawback: coalition instability.

Algorithm 1 CoalitionDecisionMaking

```
if (myRole = INDEPENDENT) then
    /* Strategy 1 */
    joinCoalitionWhenWorst(best_neighbor);
end if
if (myRole = COALITION_MEMBER) then
    /* Strategy 3 */
    leaveCoalitionWhenIsolated();
    /* Strategy 5 */
    switchCoalitionWhenWorst(best_neighbor);
end if
if (myRole = LEADER) then
    /* Strategy 8 */
    disbandCoalitionWhenBad();
end if
mutation(p_mutation);
```

Algorithm 2 The new coalition formation algorithm employed by each agent

```
1: interactWithNeighbors();
2: if (myRole ≠ LEADER) then
3:     spread(⟨[tax,p_rebellion],payoff⟩,p_spreading);
4:     [tax,p_rebellion] ←select(spreadings);
5:     innovate([tax,p_rebellion],p_innovation);
6: end if
7: coalitionDecisionMaking();
8: if (myRole = COALITION_MEMBER)
   & (tax<leader.getTax()) then
9:     leaveCoalition(p_rebellion);
10: end if
```

3.2 A Consensus Mechanism for Stable Coalitions

After section 3.1 the only issue remaining that prevents full cooperation is coalition instability. Therefore, in what follows we propose to extend the coalition formation approach (in algorithm 1) to endow it with capabilities to minimize instability. However, to accomplish this we must first understand exactly what we are trying to minimize.

3.2.1 Rebellion vs. Mutation

Along this paper we have found that mutation is both a nuisance and a crucial factor for the coalition formation process. However, when analyzing its effects, we realized that the "mutation" employed by the base approach is actually a merge of two different concepts: classic mutation (a random change in the agents' properties) and *rebellion*. The former, has been well studied in the literature [12] and affects agents' actions to play and/or the taxes to charge, whereas the latter is the probability of an agent to become a rebel (leaving its coalition). Thus, in the base approach when mutation occurs in an agent, it randomly changes its actions and taxes, and it prompts the agent to leave its coalition (if applicable). That is to say, both random changes and rebellion occur concurrently. Nonetheless, rebellion (achieved by mutation in previous experiments) is the actual factor that is crucial for the coalition formation process. Hence, it must be treated as a separate entity if we want to minimize the instability resulting from it.

The importance of a rebellion capability is not hard to understand. We have discussed before that larger and stronger coalitions emerge when agents leave their current one to join others. However, the leave or switch coalition strategies do not activate that frequently, and it is actually the rebellion probability the factor that often drives agents to leave their coalitions. This is akin to the not always logical real-life rebellion, e.g. humans may rebel from a social group without actually knowing if there is something better somewhere else. However, as the instability in all previous experiments shows, continuous/constant rebellion is detrimental to agent coalitions. Thus, we propose that, to minimize instability, agents need to adjust their rebelliousness according to their needs (e.g. their payoffs).

3.2.2 The Consensus Mechanism

Rebellion is necessary during the coalition formation process. Nonetheless, it induces instability once a single coalition emerges. Therefore, agent rebelliousness needs to be controlled by the agents themselves accordingly (i.e. only rebel when necessary). Not only that, since agents are distributed entities, rebellion must be controlled distributedly.

However, if we intend for rebellion to only occur when necessary, we firstly require to give rebellion a motive within the agent, i.e. why should an agent rebel? That is to say, rebellion needs to be dependent on some other property or characteristic of the agents. In the coalition formation process, dissatisfaction with respect to the taxes to pay provides a very logical and reasonable motive for rebellion. Therefore, we propose that an agent may only rebel once its coalition leader is charging more taxes than what the agent is willing to pay. Nevertheless, in both the base approach and in algorithm 1 the agents pay the taxes that the leader charges unconditionally. Hence, to relate taxes and rebellion the agents need to have the notion of how much they are willing to pay, i.e. a *tax threshold*. Moreover, like the rebellion probability, this tax threshold should also be decided by the agents themselves.

In human culture rebellion often occurs as a social movement. Individuals are more likely to rebel if their peers are rebelling, or are more likely to be satisfied with their taxes if their neighbors are satisfied. In other words, rebellion can be regarded as a collective decision. To that end we propose to employ a collective adaptive approach to reach a consensus about the rebellion probability and tax threshold. This proposed collective approach, inspired on the social contagion phenomenon [6], is designed to collectively emerge conventions/consensus about properties common to the agents of a MAS. Under this approach agents with *good properties* (ones that help them improve their payoffs) are more likely to spread them to other agents. For the coalition formation scenario, agents attempt to spread their rebellion probability and tax threshold. For instance, an agent spreading that its tax threshold and rebellion resulted in a high payoff, is likely to persuade other agents to adopt that threshold and rebellion.

Algorithm 2 outlines to the coalition formation algorithm designed to achieve full cooperation and closely maximize the individual agents' payoff on complex networks. The consensus mechanism is included in lines 2-6. Each non-leader agent firstly attempts to spread, with probability $p_{spreading}$, its rebellion and tax threshold using its payoff as an evaluation metric. This is followed by each agent having to decide which of all the incoming spreadings to take (line 4). In our case, an agents always takes the incoming spreading with

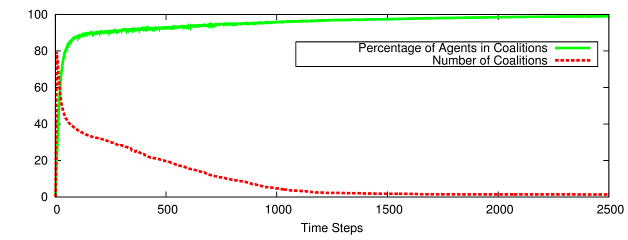

Figure 4: Coalition evolution with consensus on small-world topologies.

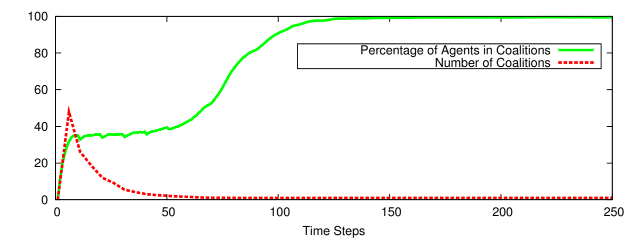

Figure 5: Coalition evolution with consensus on scale-free topologies.

highest payoff (elitist selection). Finally, the rebellion probability and threshold are randomly changed with probability $p_{innovation}$ (line 5).

3.2.3 *Sustaining Cooperation*

To evaluate the new capacity embedded into the agents, we ran experiments using a moderated spreading probability (0.2) and a low innovation rate (8×10^{-4}). Additionally, the rebellion probability and tax threshold take on values in the range (0,1).

In general, the experimental results showed that with algorithm 2 most agents in the MAS receive high payoffs. Specifically, for both topologies a *stable* single super coalition emerges with a leader that charges low taxes.

The experiments on small-world topologies (depicted in figure 4) show that initially (less than 50 time steps) agents arrange themselves in different coalitions (~ 80), which promptly start to disappear into a *single coalition*. Specifically, the single leader emerges in just ~ 1100 time steps, and around time step 2000 most agents ($\sim 99.5\%$) are already part of the single super-coalition. In other words, a single stable coalition arises such that, almost no agent leaves (very low number), and where agents have a high payoff ($\sim 93\%$ of the maximum, as shown in figure 3). Moreover, the time needed to emerge such coalition is faster than before ($\sim 60\%$ faster, see subsection 3.1.2). These results are achieved through the emergence of low tax values ($\sim 2.5\%$ of the total payoff) together with an extremely high rebellious capacity ($\sim 55\%$). This combination translates to the lemma: "low taxes or rebellion!", which the leaders are forced to comply.

Regarding scale-free topologies (see figure 5), a single coalition is achieved faster than before (in less than 200 time steps vs. ~ 300). What is more, the coalition now is completely stable (very unusual for an agent to leave it) and the taxes ($\sim$20% of the agent's total payoff) are lower than when employing the base approach or just algorithm 1 ($\sim 44\%$ in both cases). When comparing with small-world, observe that the process is similar (an initial peak in the number of coalitions that then decreases into a single coalition) but much faster (10 times faster).

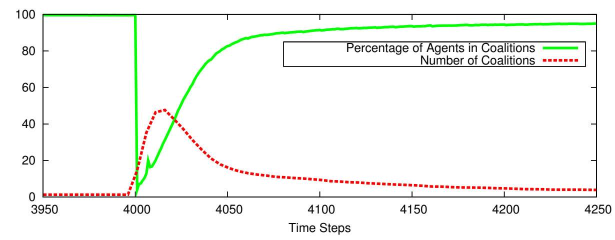

Figure 6: Fault resilience on small-world topologies.

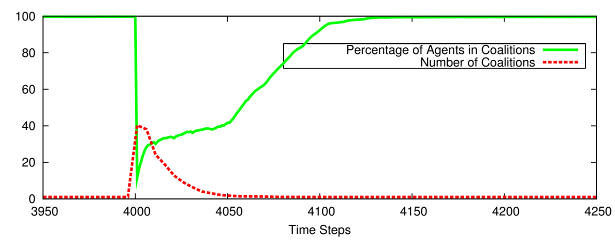

Figure 7: Fault resilience on scale-free topologies.

Finally, although full cooperation is closely achieved, it comes with an associated cost: *extra communication*. The spreadings sent by agents represent additional messages. Nonetheless, to emerge a single coalition each agent in a scale-free topology needs to send only ~ 4 messages, while an agent in a small-world topology needs ~ 40 messages.

3.2.4 *Fault Resilience*

Notice that, in actual (real-world) environments, our cooperation scheme has an associated risk: the existence of a single leader. If the leader agent becomes a target of malicious attacks or fails by chance, all the agents in the coalition will immediately become independent. Therefore, the experiments in this section were designed to evaluate the resilience of our approach to such failures.

To that end we repeated the experiments in the previous section, but now attacking the leader once the single coalition is stable. Specifically, after 4000 time steps (once a single coalition has emerged and proven to be stable) we completely removed the leader agent from the MAS to simulate the leader's failure.

Figures 6 and 7 depict how agents react after the leader is taken down. In general, observe that the response is similar for both topologies. After the leader disappears and all agents become independent, multiple coalitions begin to emerge. However, these coalitions do not last very long (less than 50 time steps) and rapidly start to disband so their members can join a single super-coalition. The peaks in the small-world and scale-free *number of coalitions* plots depicts this transition. The single super-coalition emergence occurs faster because agents already have some good estimations of the tax threshold and rebellion probability (i.e. they are not searching for these values from scratch). Furthermore, once again agents on scale-free are quicker to emerge a single coalition than the small-world ones (< 100 against < 600 time steps). When compared with the previous experiments (figures 4 and 5), emergence is twice as fast on scale-free and four times faster on small-world.

Overall, the experiments show that coalition emergence with a consensus mechanism is resilient against leader failures, which was also one of our main objectives (mentioned at the beginning of this section).

4. CONCLUSIONS

In this paper we confirmed that coalitions indeed facilitate cooperation between self-interest agents. However, we found that the coalition formation process is considerably sensitive to the MAS topology. In particular, to the complex network topologies that model actual-world environments.

To that end we proposed a new distributed, lightweight and efficient coalition emergence approach. We showed that agents on complex network topologies employing this approach can achieve full cooperation by grouping into a single super-coalition. Moreover, agents in this super-coalition can maintain cooperation over time in exchange of some significantly low tax, which is agreed by the agents themselves (thus increasing their overall profits). Hence, closely maximizing their payoffs.

In our experiments, we determined that *rebellion* is a crucial factor for coalition emergence. Through rebellion, smaller and unprofitable coalitions disappear so that bigger ones can rise. Moreover, the agent population can use rebellion to pressure leaders to decrease their taxes. Consequently, increasing competitiveness among leading agents. This contrasts with Axelrod's model [3], where leaders were the ones who pressured the population to the point of extortion. Overall, our proposed approach results in a faster single-coalition emergence and in lower taxes for the population as a whole. Nonetheless, the emergence time and the taxes still vary depending on the topology.

On the one hand, the lowly-clustered, with highly-connected hubs, structure of scale-free topologies gives hub agents an inherent advantage over the rest of the population. Specifically, hub agents can promptly emerge as leaders, dominating the population and getting away with somewhat higher taxes. On the other hand, in the highly clustered small-world topologies, any agent has the potential to become a leader, thus sparking a fiercer and longer (time-wise) price war, which results in much lower taxes.

Furthermore, we determined that commitment to either other agents or leaders (and employed in [3] and [5]) is not essential for coalition formation and maintenance. Even without commitment, a single coalition can emerge and be sustained over time as long as the agents are satisfied with their leaders, which is likely to occur since a leader is always under the threat of rebellion when misbehaving.

Finally, even though it is known that employing a leader based super-coalition introduces a single point of failure into the MAS, our proposed approach is resilient against leader failures (e.g. DOS attacks, disappearance, removal). However, we plan to study how multiple coalition could emerge when the population is divided by goals.

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