An adaptive trust model for achieving emergent cooperation in ad hoc networks.

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Abstract Cooperation is a fundamental part of both the Next Generation Networks (NGNs) and the expected applications of Industry 4.0. In such systems, there is no centralized control, and the system components require self-organize themselves to capturing, processing and analyzing real-world information with the purpose of delivering useful data to the final user. In this article, we aim to explore the cooperation mechanisms that could be used in the next generation of communication systems to produce collective behaviors that allow the member of the system join efforts to achieve individual and collective goals in environments without a centralized controller. We used socially inspired computing to introduced an adaptive trust model based on a theoretical analysis of cooperation through game theory and genetic algorithms. The results show cooperation in the system can adapt itself even in environments with dynamic populations, selfish agents and failures in the communication process.

Keywords Self-organization, ad-hoc networks, trust, cooperation, socially inspired computing.

1 Introduction

The recent industrial revolution born under the Industry 4.0 concept has generated several theoretical and technological challenges for the future communication systems [24]. One of the main issues related to these technologies is the management, analysis, and control of massive data flows which could overload the network not only in the physical but also in the logical layers [51, 21, 49]. This situation, known as the Big Data problem, is an active research area in computer science and engineering and has increased the market expectation significantly during the last years due to the social benefits of capturing, processing and analyzing a lot of real-world information [16]. However, these new technologies are facing several challenges because of the complexity related to the theoretical treatment of the information flows which are easily captured, but difficult to process [16].

As a consequence, essential advances in this field are expected in the next years in order to make easier for technological systems to support decision processes and deliver useful information to the final user. The idea is giving ontological content to different data fields in order to turn our normal social environment into an intelligent computational system [50, 27]. Besides, in recent years there has been an active debate about the role of humanities in the academia animated by the idea that it is necessary to improve the relationship between social sciences and engineering. During the last years, the discussion has included philosophy and computer science with the purpose of improving the understanding of intelligence mechanisms on a XXI Century world. Max Tegmark [43], remarks the role of humans beings in the artificial intelligence era, in which information and knowledge could be considered as the core of the next generation of technological developments.

In this regard, it is possible to identify at least five different kinds of intelligence according to the Tegmark definition; in this case, intelligence is defined as the capacity to achieve complex objectives. For example, a *Narrowed* intelligence reacts in the presence of specific and limited problems and solves them at least as well as a human being; a *General* intelligence implies that machines could achieve practically any objective and manage any cognitive activity. Also, there is an idea of a *Universal* intelligence that could be reached anywhere using multiple methods to access data and resources; a *Singular* one that could compete with human intelligence and finally the *Strong* intelligence that could easily overcome human capacities. We are trying to find unique mechanisms that enable the next steps in the path to reach a relationship between social sciences and engineering, in particular, among philosophy of mind, telecommunications, and the economic theory. These topics allow us to explore this *super intelligence* reported by [9] as the emergent properties found in the decision process of self-organized systems.

Also, it is required for the NGNs to include most flexible devices and protocols to allow better interactions between the computational infrastructure and the goals of the final users. In general terms, computational devices and algorithms are used by people and organizations, in local, personal and wide area networks as tools to interact with the social systems they belong. However, the accomplishment of tasks depends on interaction and interoperation of possible unreliable and conflicting components, and as a result, the system is relying on self-organization mechanisms to complete its purpose. The results of this paper show cooperation may emerge even in scenarios in which agents do not have a cooperative strategy *per se*. Moreover, the absence of a centralized controller and the increasing autonomy of the devices make necessary to include meta-cooperative mechanisms inside engineering developments for improving the system capacity for solving problems through collective actions.

Accordingly, our aim in this paper is to explore the cooperation mechanisms that could be used in the future communication networks to produce collective behaviors that allow both final users and computational process join efforts for capturing, processing and analyzing real-world information in environments without a centralized controller or other orchestrations forms. We focus only on ad hoc networks [32]. These systems are created on demand for a wide specific purposes and operate without any pre-established infrastructure. We used socially inspired computing to introduced a theoretical trust model and configure scenarios in which all agents feel free to interact with each other and cooperate according to their needs. Our model is based on a theoretical analysis of the cooperation process through game theory and genetic algorithms; this research can be seen as an extension of the works presented in [26, 20].

The rest of the paper is organized as follows. In Section 2 a brief introduction to ad hoc networks and cooperation models is presented to put in context our model. Section 3 and section 4 present a theoretical model of trust through no-cooperative games and genetic algorithms. Section 5 shows the performance and results of the proposed simulation scenarios. Finally, section 6 concludes the article.

2 Related work: cooperation models in ad hoc networks

Ad hoc networks are self-organized computing systems formed by wireless mobile devices with limited resources. It can be seen as a set of autonomous components operating into a dynamic environment; each component operates based on the local information provided for its neighbors, and the system functionalities arise as an emergent behavior due to interactions among nodes, users and applications [32, 31]. In such networks, cooperation process can be understood as a requirement to solve problems through collective actions, in which the accomplishment of the tasks depends on interaction and interoperation of unreliable and conflicting components. In the following section, we briefly review cooperation models and social dilemmas to put in context our model.

2.1 Cooperation models

Cooperation models in ad hoc networks can be divided into two categories according to the method they use to produce collaborative behaviors: credit-based models and trust models. The first one is based on an economic incentive to promote interaction among network components. In such models, networking tasks are treated as services that can be charged to nodes, users, and applications through virtual currencies. Some representative proposals of these models are presented in [10, 25]. On the other hand, models based on trust and reputation can work in decentralized environments and deal with free-riders and selfish nodes; if a node is not willing to cooperate, the affected nodes may deny cooperation in future interactions. Likewise, trust and reputation measures may be dynamic and evolve according to environmental conditions to produce groups of nodes according to their interests [15].

Furthermore, the conditions required to achieve cooperation in self-organized systems, have been widely studied by game theory. It studies models of conflict and cooperation between rational decision-makers in systems composed of co-dependent and interdependent components. In the context of the ad hoc networks, game theory has been used to deal with challenges related to resources distribution, information control, and selfish behaviors through no-cooperative games [1, 28]. Besides, cooperation can emerge in scenarios in which agents do not have an initial cooperative strategy, making necessary to analyze the set of conditions in which a game may become cooperative, unviable or unprofitable [29]. For instance, Tit for Tat (TFT) provides a well-known framework to achieve emergent cooperation based on the past behavior of other players. However, even TFT can be defeated whether a large population of selfish nodes appears, or because of failures in message exchange [40, 30]. A complete analysis of these proposals is presented in [4, 3].

Similarly, cooperation patterns of living systems (biological, social, political and economical) have been analyzed for many disciplines like philosophy, social science, artificial intelligence, and mathematics in order to inspire new technological solutions for artificial systems [5, 48]. Nevertheless, the majority of these proposals use an individual methodological approach and can be divided into five categories [47]: Middle Age Contractualism, Classic Prosperity Theory, Neo-classic Economy Theory, the Individualism associated to the Situational logic of Karl Popper and the Structuralism derived from James S. Coleman. All these approaches face several challenges to archive cooperation under uncertainty conditions in highly dynamic environments. In contrast, the empirical results of social sciences show that decision makers do not make rational decisions all the time, and the limited rational theory may explain and go forward to the incompatibility problems between methodological individualism and neoclassic paradigms. This approach gives an opportunity to build new cooperation models for artificial systems [2, 42].

2.2 Social Dilemmas

Social dilemmas are situations in which individual rationality leads to collective irrationality, i.e, when a reasonable individual behavior leads to a situation in which everyone is worse off. There are many scenarios in which two agents need to deal with a situation of defecting or nor not each other in the presence of common goals in an uncertain environment [18]. Likewise, a group of agents facing a social dilemma may completely understand the situation, may appreciate how each of their actions contributes to a negative outcome, and still be unable to do anything to change the result. In this regard, social dilemmas are marked by at least one other outcome in which everyone is better off [17, 13, 6].

Also, groups of interest and communities are closely defined by their capacity to manage local resources and imparting justice for any subgroup that belongs to them [33, 35]. There is a considerable part of rational theory related to social dilemmas that allow us to inspire mechanisms to rule resources and tasks distribution in artificial systems. What we can do is to create scenarios in which justice may be familiar to all agents through a function that represents a set of rules to manage distribution and cooperation issues. Besides, the approaches based on methodological individualism face a significant challenge when decision-makers need to gather information to reveal the conditions of the environment [2]; the data could be socially spread but not useful because of it needs to be absorbed by agents. As a result, the limits in the capacity of an agent to obtain information are substantial barriers for its diffusion, setting complex scenarios in which meta-strategies are needed [39].

3 An adaptive model of trust

Cooperation in ad hoc networks is needed for solving problems through collective actions and ensure communications among the system components. The operating conditions of ad hoc networks make necessary give to the nodes the ability to adapt their behaviors to unexpected situations and possible selfish behaviors. In this regard, genetic algorithms and evolutionary computing have been applied to face these challenges using the adaptive properties related to the natural evolution of living systems. Examples of these models can be found in [12] as a technique for improving the diagnosis of breast cancer. In [44] for identifying and classifying diabetes. Also, they have been used for facing problems like short-term load forecasting [34] and optimization of Stirling Energy Systems [19]. Nevertheless, in the context of this research, we use the proposal presented in [26], which codify strategies in a 16 bit code as is presented in Table 1. This algorithm includes a trust level for every member of the systems based on their previous interactions, where "D" means defect and "C" means cooperate.

Table 1. Strategy example 0001 0011 0111 0111

Agent trust level	0	0	0	0	1	1	1	1	2	2	2	2	3	3	3	3
Transmission status - 2	D	D	C	C	D	D	C	C	D	D	C	C	D	D	C	C
Transmission status - 1	D	C	D	C	D	C	D	C	D	C	D	C	D	C	D	C
Strategy	D	D	D	C	D	D	C	C	D	C	C	C	D	C	C	C

According to those conditions, two factors determine the level of trust: the direct interactions among nodes and the cooperation process they observe from their close neighbors. In such case, an agent does not interact directly with others but can perceive their behaviors (this can be seen as the agent's reputation, which is created based on its past actions)[26]. Thus, a node can modify its level of trust depending on its interactions and the responses observed in the environment. Besides, we also consider selfish agents which only cooperate if they are source nodes and never change their strategies; our aim is to test how an adaptive agent can adjust their strategy to face a group of agents that only want to take advantage of the network.

Table 2. Payoffs for source node

Source node payoffs Transmission status	
Successful	5
Failed	0

Furthermore, the performance of the nodes is evaluated with the purpose of measuring the fitness function for every member of the system; this process gives to each node a score that changes under two different events: first, if an agent tries to deliver a packet to another node (acting as the source node), it receives points according to table 2. Second, if an agent is part of the path chosen by a source node to deliver the packet (acting as an intermediate node), it updates the scores according to the table 3. This process allows us to test all strategies according to their success in the network.

Table 3. Payoffs for intermediate nodes

	Intermediate node payoffs Trust level of the source node			
Cooperate	3	2	1	0.5
Discard	0.5	1	2	3

Finally, the evolution process takes the fitness function to determine the next generation of strategies. This process is made of two stages: crossover and mutation. The crossover process chooses the parents through a roulette wheel process, in which a selection probability p_k is assigned to each strategy. The parents are selected considering the probability distribution resulting of divided the fitness value of each node into the total fitness in the network [26]. Afterward, the crossover process takes half the genetic code of each parent to create a new strategy. The mutation process changes a bit of the new strategy with a small probability with the purpose of including randomness in the process.

4 Simulation Scenarios

In order to evaluate the performance of the model, three simulation scenarios were proposed. The difference in each case is the percentage of selfish nodes (those who never cooperate) regarding adaptive nodes (those who can change their strategy according to the network conditions). Additionally, we consider different network topologies, errors in the message exchange and a dynamic population of adaptive nodes. A description of each scenario is presented in Table 4.

Table 4. Simulation Scenarios

Simulation scenarios			
Figure	**Genetic Population**	**Error**	**PMP**
1	100%	0%	10, 25, 50
2	80%	0%	10, 25, 50
3	50%	0%	10, 25, 50
5	80%	20%	25, 50
6	50%	20%	25
7	80%	30%	50
9	Variation	0%, 10%, 20%	25

4.1 Scenario 1: no error

In this scenario we test the adaptive trust model changing the percentage of selfish agents in the network. The result of the experiment with a population of 100% of adaptive nodes is presented in Figure 1. Figure 2 shows an experiment in which we have 80% of adaptive nodes and 20% of selfish nodes. Figure 3 presents the results for an experiment with 50% of adaptive nodes and 50% selfish nodes. We aim to analyze the evolution of strategies in three-different lapses of time (pmp), i.e., the number of interaction after nodes will evolve. Also, all results present the maximum theoretical cooperation value. Errors in the communication process were not considered during the simulation.

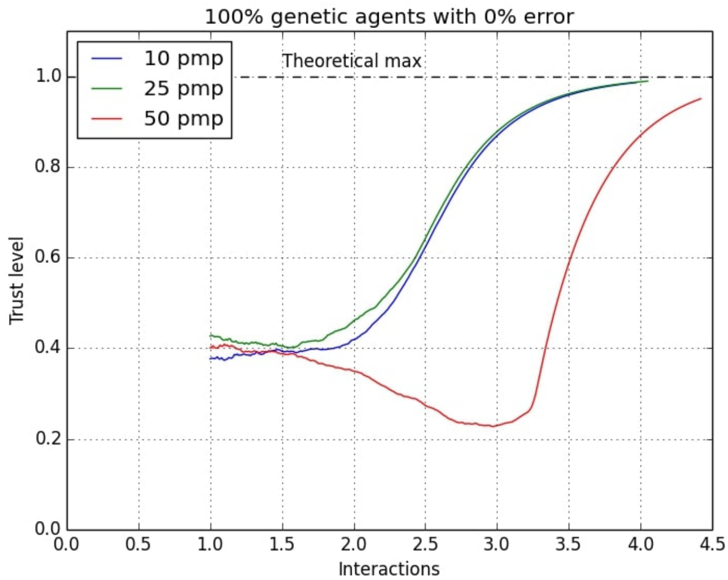

Fig.1 100% adaptive nodes**.**

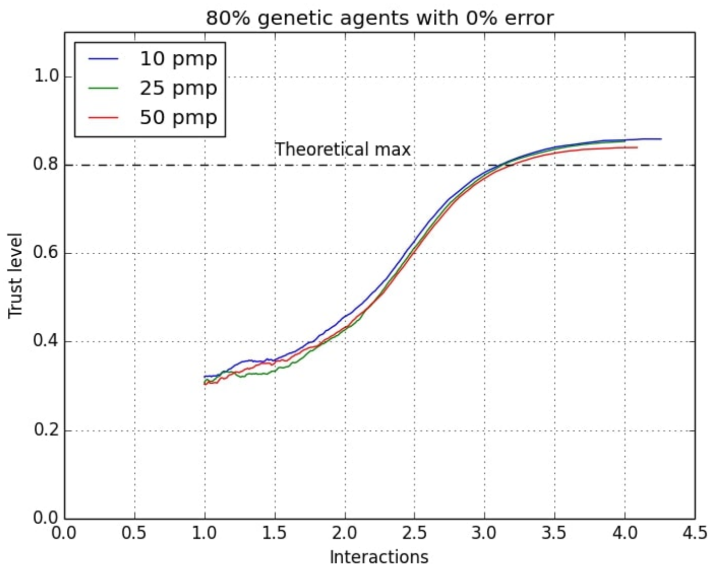

Fig.2 80% adaptive nodes - 20% selfish nodes**.**

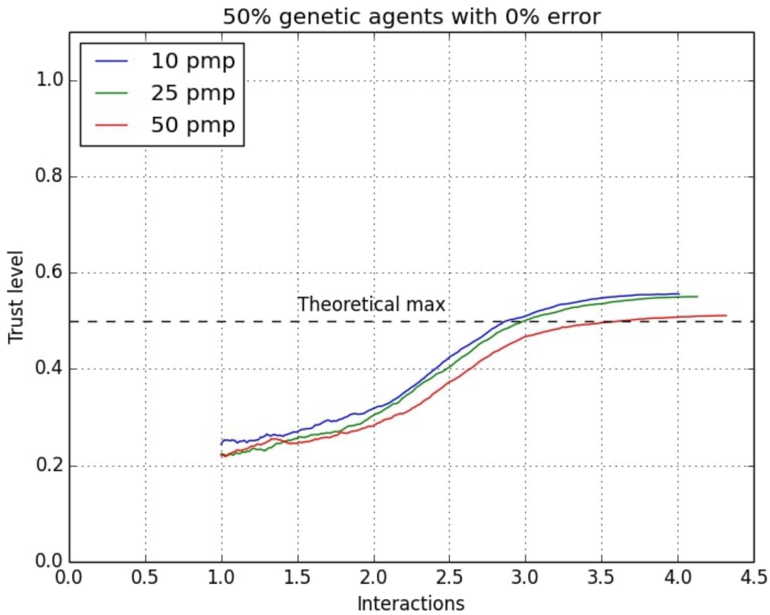

Fig.3 50% adaptive nodes - 50% selfish nodes.

4.2 Scenario 2: error in the communication process

In this scenario, the adaptability of the trust model is tested introducing probabilistic error in the communication process. This error represents any situation related to routing problems, message exchange, accuracy in the agents' responses and so on. We aim to simulate failures that may occur during the normal operation of the network. It is important to mention that due to the dynamic nature of the ad hoc networks these kind of problems are a regular part of the operating conditions and need to be considered during the evaluation of the model. Given those requirements, the same cases proposed in the first scenario were considered, but we include probabilistic error during the cooperation process (For example, a node who cooperates but their neighbors perceives that it does not). Figure 4 presents the results with 80% of adaptive agents and a probabilistic error of 20%. The figure 5 shows the results with 50% of adaptive agents and a probabilistic error of 20%. Figure 6 presents the results with 80% of adaptive agents and a probabilistic error of 30%.

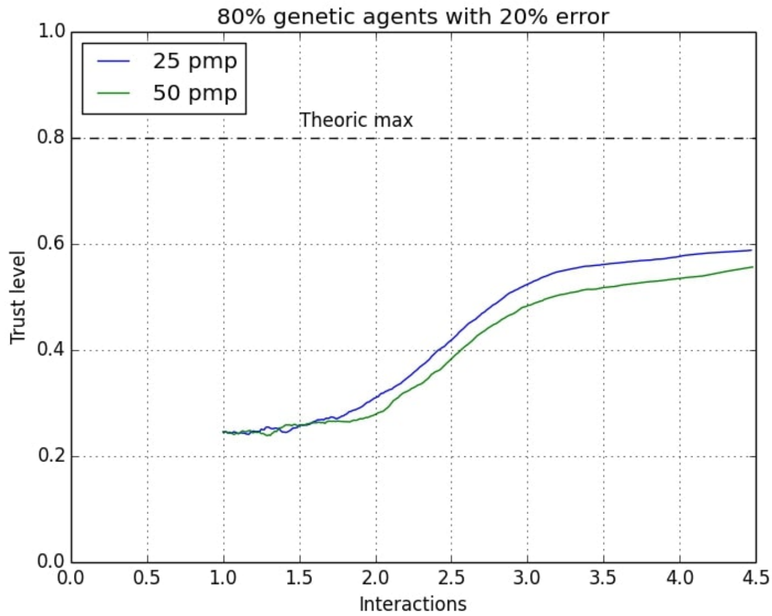

Fig.4 80% adaptive nodes - 20% error.

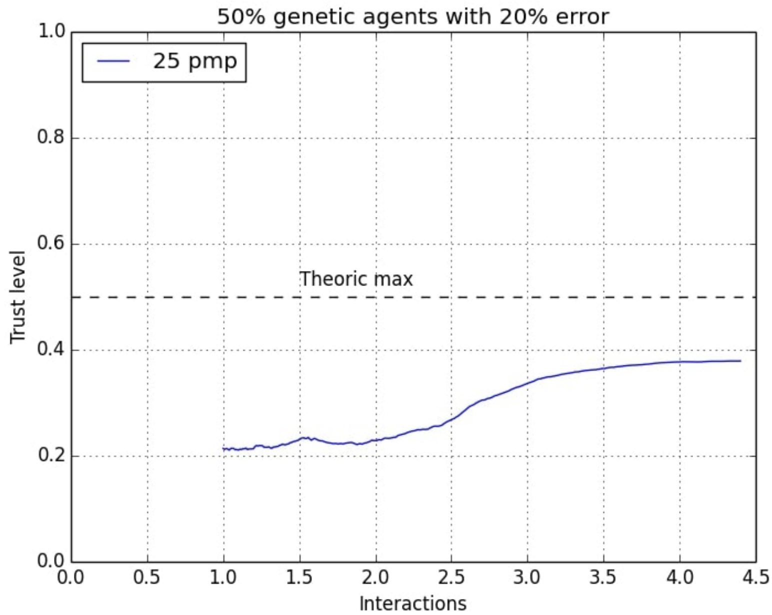

Fig.5 50% adaptive nodes - 20% error.

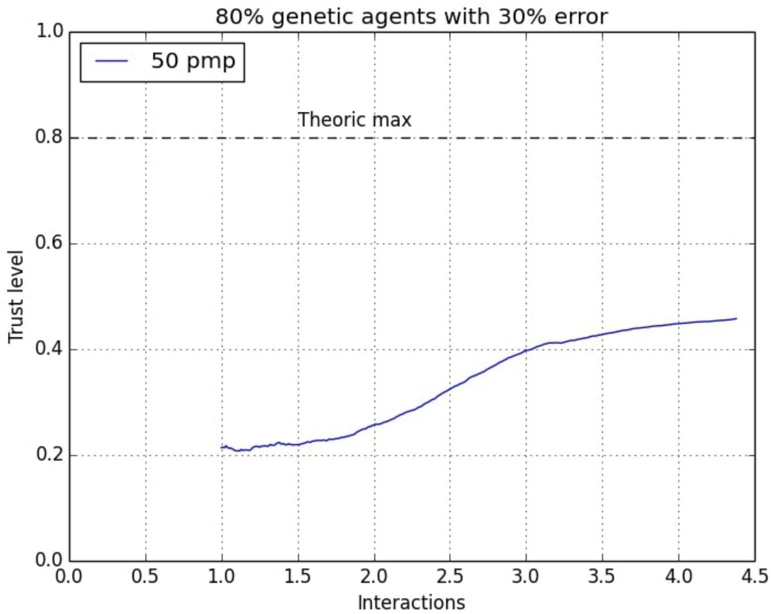

Fig.6 80% adaptive nodes - 30% error**.**

4.3 Scenario 3: a dynamic population

The advantage of the evolutionary approach used in this model is to provide adaptive features that allow the nodes to deal with unexpected environments. In this regard, in this scenario, the population of selfish and adaptive agents is changed during the simulation. First, the simulation begins with 50% of adaptive nodes, then, after 1000 ticks (in this case a tick refers to a round in which a fixed number of packets were delivered successfully in the network) the number of adaptive nodes changes to 80% (To do this, the 30% of new the new adaptive nodes receive a random strategy to start evolving. Then, after 2000 ticks the network change to 100% of adaptive nodes and returns to 80% after 3000 ticks. Finally, after 4000 the network return to its original state; 50% of adaptive nodes. This experiment was performed with probabilistic errors of 0%, 10% and 20% with the purpose of observing the behavior of the model under frequent changes in the agents' population. All result are shown in Figure 7.

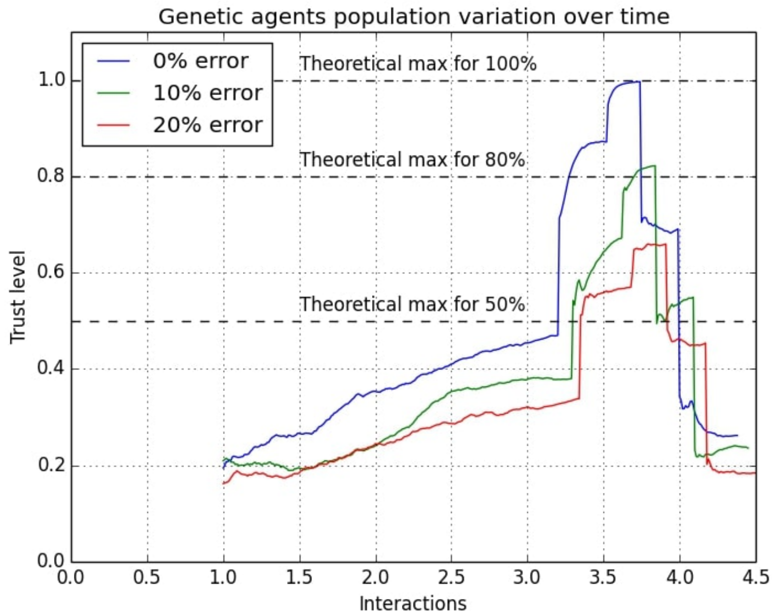

Fig.7 Genetic algorithm with a dynamic population over time**.**

All simulations show the adaptation process in the nodes' strategies. The adaptive nodes increase the cooperation among them and decrease the cooperation with selfish nodes. Scenario 1 shows results very close to the theoretical maximum, and it is possible to observe the adaptive behaviors along the simulation. Also, some experiments report cooperation values above of theoretical maximum; those results represent the proportion in which the selfish nodes are taking advantage of the system. Scenario 2 shows the consequences of the communication errors in the network performance; the result shows adaptive agents cannot deal with errors as we expect; however, the model keeps working under acceptable parameters given the operating conditions. The results presented in the Scenario 3 verify the proper response of the model to a dynamic population of selfish and adaptive agents. This scenario allows us to guarantee that the results not depend on the initial conditions of the simulation.

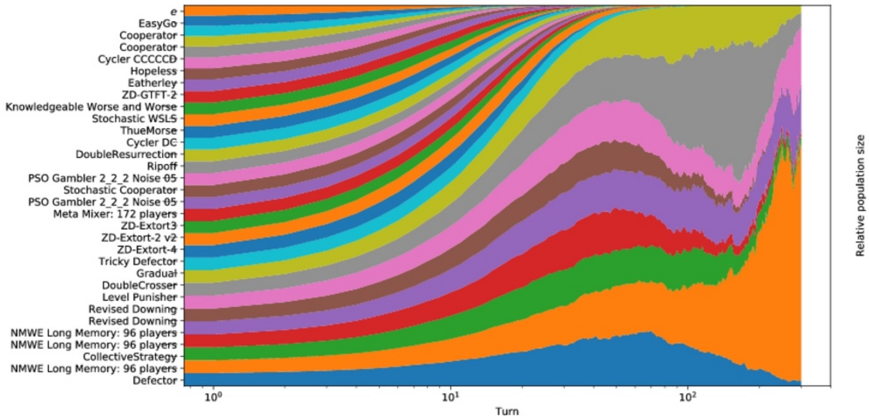

Fig.8 Populations dynamics of a tournament**.**

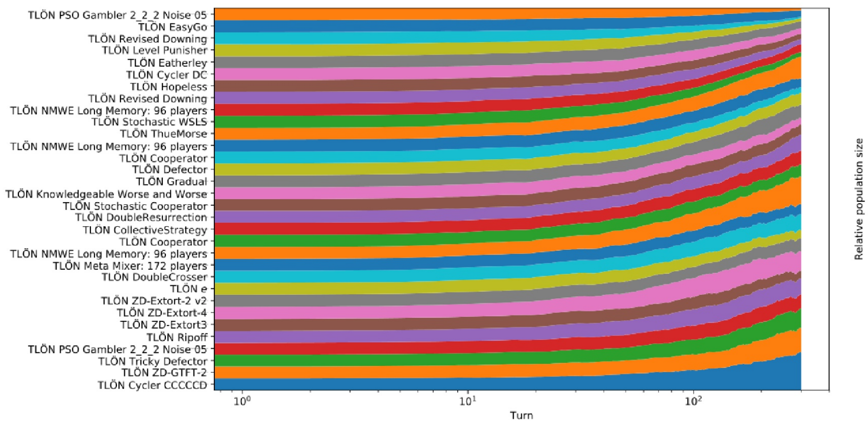

Fig.9 Populations dynamics of a tournament with n=0.3.

5 A meta-strategy on cooperative-competitive games

In the above section, we showed that nodes could adapt their strategy to variations in the behavior of other agents. However, it is possible to improve not only the payoff of the individuals but also the payoff of a community (in this research a community can be understood as a group of agents that share a set of beliefs or goals). According to those conditions, a coordination process is needed in the system to achieve collaborative behavior among different groups of individuals in which cooperation and competition coexist at the same environment [23].

Consequently, the next step in this research is present a multi-agent system in which this problem is analyzed through a coalitional game approximation. In this case, the social dilemma is faced including the concepts of sympathy and commitment during the decision process in which an agent choose if cooperate or not. A detail description of this model can be found in [20] and [46, 45].

The traditional approach for analyzing coalitions is defined them as a group of agents and represented by full connected graphs in which rational assumptions about individuals are not defined at all. This approach forces the agents to assume (at least into their coalitions) complete information scenarios and turn the decision process into an (NP) complex problem [11]. However, inspired by H. Simon [41, 42] and A. Sen [38, 36, 37] we propose that is possible to avoid negotiation process when it is not needed, or could be assumed by clarifying the social connections in the members of the system. Given those conditions, the rationality is naturally limited, and the social links in the coalition are mainly obtained through the sympathy and commitment connections [37]. Those scenarios are tested by game theory analysis letting all agents assume an aleatory strategy, but assuming cooperation inside their coalition.

According to the results presented in Figure 9 the population dynamics shows consistency between the diversity of communities and cooperation processes (this result can be compared with Figure 8, in which is possible to observe a higher variation in the population of the communities). The Y-Axis shows the random strategy used by the 30 groups of agents, and the X-Axis represents the game round number when the strategy has the TLÖN prefix; that means that this agent implements the coalitional meta-strategy. So, the more cooperative the system, the more diverse it could be. Furthermore, diversity is a desirable property in self-organized communication systems like ad hoc networks, and it is related to a significant number of issues like security, clustering algorithms, routing [8] and medium access control [14]. Furthermore, the results show agents in a coalition could get a better performance regarding other agents that stay alone. This result may represent an improvement in the satisfaction of needs related to the coordination processes in artificial system in which there is no centralized controller.

6 Conclusions

In the future communications networks, cooperation will be a fundamental part of the network performance in environments in which there is no centralized control or other orchestration forms. In this article, we have shown that it is possible to combine non-cooperative, coalitional games and genetic algorithms to achieve emergent cooperation in ad hoc networks. We used socially inspired computing to proposed a theoretical trust model and configure scenarios in which all agents feel free to interact with each other and cooperate according to their needs. The results show a better average payoff compare with selfish nodes and pure rational strategies. Also, it is possible to verify the adaptation process in the network when there are changes in the operating conditions.

As we have seen, there are many exciting challenges to research in this field. For example, it would be useful to find how does an individual behave in high-risk scenarios in which no pay matrix is provided or is not easy to assume. These cases are everyday situations in markets with high variability where no oligopoly, monopolistic or regulated scenarios appear. We proposed a model in which the coalition acts as a player on an oligopoly game, transforming itself at the end on a monopoly to avoids the uncertainty and the cost of the cooperation process. However, social preferences could not be assumed in an absolute way since they could not always be linked to the individual preference; someone inside the coalition should support them [7]. So looping on these two kinds of expectations and letting them change over time, there will be a relationship between rational theory and this coalitional approximation. Nevertheless, it is necessary to develop more in-depth research in dynamic behaviors for coalition games.

Moreover, it is necessary to prove that the complexity of the problem will not increase if we use the model proposed above. Also, it is required to verify the implications of misbehaviors in the cooperation process and how they may affect the evolution of the node strategies. In this regard, it is possible to model some uncertain aspect in the network like errors, misbehaviors, failures in the message exchange, etc., if we include noise as part of the simulation parameters. This approach is suitable to mitigate some distribution problems on two-players games, but it should be analyzed with three or more player with opportunistic behaviors [22].

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