Mechanisms for Social Norms Support in Virtual Societies

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Abstract. Social Norms proliferate in societies as a mechanism for self- organization. This kind of norms are not enforced by a central authority and the individuals of the society are those responsible for their generation and maintenance. The maintenance process is what is known as *norm support* and is supported by several mechanisms like for example laws, social proof, dominance, etc. We believe that agent based simulation is a suitable technique for investigating this topic. In this paper we present a simulated society of virtual agents which helps us studying the effects of a social evaluation like the Image as a mechanism to ensure the norm support process in a society with liars. Intimately related, we also introduce the concept of *Visionary* agent (individual that can evaluate norms before trying them in the real society) and study its effect on simulations.

1 Introduction and Related Work

Social norms are part of our everyday life. They help people self-organizing in many situations where having an authority representative is not feasible. On the contrary to institutional rules, the responsibility to enforce social norms is not the task of a central authority but a task of each member of the society. From the book of Bicchieri [1], the following definition of social norms is extracted: "The social norms I am talking about are not the formal, prescriptive or proscriptive rules designed, imposed, and enforced by an exogenous authority through the administration of selective incentives. I rather discuss informal norms that emerge through the decentralized interaction of agents within a collective and are not imposed or designed by an authority". Social norms are used in human societies as a mechanism to improve the behaviour of the individuals in those societies without relying on a centralized and omnipresent authority. In recent years, the use of these kinds of norms has been considered also as a mechanism to regulate virtual societies and specifically societies formed by artificial agents ([2], [3], [4], [5]). From another point of view, the possibility of performing agent based simulation on social norms helps us to understand better how they work in human societies.
One of the main topics of research regarding the use of social norms in virtual societies is how they emerge, that is, how social norms are created at first instance. This has been studied by several authors ([6], [7], [8], [9]) who propose different factors that can influence this emergence. We divide the emergence of norms into two different stages: (a) how norms appear in the mind of one or several individuals and (b) how these new

norms are spread over the society until they become accepted social norms. We are interested in studying the second stage, the spreading and acceptance of social norms, what Axelrod [6] calls *norm support*. Our understanding of norm support deals with the problem of which norm is established as the dominant when more than one norm exists for the same situation. In the literature we can find several works ([7], [9]) that address this problem, using a prisoner's dilemma as evaluation function, converting the problem of norm support in a coordination problem, where the agents have to learn to cooperate with the rest of the society, otherwise some kind of social punishment will be applied to them.

Our model, in contrast to those solving coordination problems, can deal with social norms that are not representable in a decision table and the rewards for following a certain norm are not known a priori. A similar approach can be found in the work of Cecconi and Parisi [10], where they also deal with a simulated resource consuming society. In their work, agents do not know beforehand how good the sets of social norms they follow are, even though the authors only consider two well differentiated sets of social norms (individual strategy or collective strategy of resource consumption). However, a society can have several (more than just two as we have already seen in the literature) sets of social norms abided by different members of the society. In the work of Sen [11], we observe that the authors present 6 different strategies (or sets of social norms), but they study the behaviour of mixed populations of these kinds of agents.

Specifically, we will study the situation where **while having initially different sets of social norms in a society, after some time, one of these sets (the one that maximizes the common goal of the society) prevails over the rest**.

For the sake of simplicity, we assume that all agents pursue the same global objective while trying to satisfy, as a second instance, its own objective. As we said, we want to study the situation where a single set of social norms, after some time, prevails over the rest. This is the first step that should allow us to study in the future more complex situations where different sets of norms sharing the same social space, with similar levels of satisfaction at the individual level, can achieve a better global result than a single dominant set. In the study presented in this paper we use a social evaluation mechanism as the image (which is the own believed evaluation of the others) as the main mechanism to facilitate the process of *norm support*. We also introduce the concept of 'visionary' individuals as a special kind of individual that by means of local simulations of the environment can foresee how a set of norms should work in the society if they were adopted as the dominant set.

2 Reference Scenario

In order to design an scenario where the usage of social norms is significant, we are inspired by real life examples ([12], [13]), where the usage of social norms is crucial for the survival of the society. The society we use for our experiments is a resource-gatherer distributed and decentralized society. All the members of the society survive by consuming resources that appear randomly in the environment and exchanging the resources among them by **abiding to a set of social norms**. Depending on the quality of these social norms, the society succeeds in the task of increasing the average life

expectancy of its members.
The application domain of this research is directly related to an ongoing research which is carried out by a group of archaeologists. We are presented an ancient historic society, already extinguished, known as *'the Yámanas'*. This society was located in Southern Argentina and is one of the groups of the societies commonly known as 'canoeros'. They lived there for around 6000 years in a very hostile environment. The main success, and reason of study, of this peculiar society is their ability of auto-organization: the *Yámanas* were able to auto-organize themselves as a hunter-gatherer society. The archaeologists consider as a hypothesis that the key of success of this society was due to their strong respect for a known set of social norms (represented as a set of myths). These social norms regulated, amongst other behaviours, the resource exchange between the *Yámanas*. From the study of Gusinde [14], we extract that social norms for resource exchange regulation only made sense in such societies when the resources to be exchanged would appear sporadically although of a large contribution when they appear (e.g. finding a whale on the beach was a huge amount of resources but it would not happen frequently). Therefore, we adapt the parameters of the simulation to this scenario.
We want to stress that even though we inspired our simulations by the previously described society, the simulation scenario is a simplification of it. Consequently, we do not intend to affirm that the results obtained out of our simulations, as they are now, are directly applicable to real societies. Notwithstanding, the results are relevant for societies of virtual agents.

3 Statement of the Problem

The problem to be addressed in the following sections is the establishment of social norms. Suppose an initial population of virtual agents where each agent possesses a set of social norms although all of them pursue the same global objective. Each agent might have a different set of norms from the rest of agents. However, from [15] we extract that *'everyone conforms, everyone expects others to conform, and everyone has good reason to conform because confirming is in each person's best interest when everyone else plans to conform'*. Therefore we are interested in scenarios where agents might converge to a common and optimum set of norms, as they pursue the same objective. Different mechanisms are supposed to ease and accelerate this process when malicious agents are present. We will focus on how image affects the process of norm stability.
Our experimental scenario is based on a society with no central authority where all the agents survive by consuming resources found in the environment. When two agents meet, they abide by their social norms in order to decide whether to share resources or not. The fact of donating resources provide the other agent with extra resources that make it survive for a longer period of time. Moreover, agents have a period of time where they can exchange their social norms in order to obtain different results. Malicious agents can lie during the communication process, trying to take advantage of innocent agents. We will verify the effectiveness of some mechanisms for the convergence of the optimal set of social norms when untrusted agents coexist in the society.
Our hipothesis are:

- **H1** - When dealing with a sincere population, agents converge to the optimal norms.

- **H2** - When dealing with an insincere population, agents need a social evaluation mechanism to converge to the optimal norms.
- **H3** - Visionaries agents accelerate the process of convergence.

4 Social Norms Formalization

All agents can perceive a finite set of *observables* $\mathcal{O}$, and each element of the set is denoted as *ob*. Every agent also has a finite set of *actions* A, and each element of the set is denoted as a. Every agent can find itself in a finite set of different *situations* $\mathcal{S}$, and each element of the set is denoted as $sit \subset \mathcal{O}$. In other words, a *situation* is a combination of different observables.
Given that, a ***social norm*** SN_i is a tuple formed by a situation and an action: $SN_i = \{\langle sit_g, a_h \rangle \mid sit_g \in \mathcal{S}, a_h \in A\}$. The combination of all the possible situations associated to an action generates a **set of social norms**.

5 Simulation Model

We use a multi-agent system for our simulation. This multi-agent system is represented as an undirected graph: $MAS = \langle A, Rel \rangle$, where $\mathcal{A} = \{Ag_1, \ldots, Ag_n\}$ is a set of *n* agents representing the vertices of the graph, with $n \geq 1$; and *Rel* the set of relations (edges) between the agents. All the neighbours at distance 1 in the graph *MAS* of a certain agent is defined as the *neighbours network* of this agent. All the agents are initially loaded with 100 resource units. The simulation algorithm is based on a discrete step timing model, where each time step the algorithm observes the state and consequent actions of each agent before ticking another time step. At every time step, the simulation algorithm runs over every agent. The order in which the algorithm runs over the agents is randomly changed each time step. In this way, all the agents are able to execute their actions, in a random order each time step, annulling any advantage of one agent over the rest. Each agent consumes one resource unit each time step as energy consumption for survival. When one agent exhausts its resources, it 'dies'. After dying, agents are able to reset themselves with initial resource conditions (after recalculating its *Average Life Expectancy* (ALE)), and to evaluate the norms they are using at that moment with the possibility to change it, like in an Evaluation Period (explained in Sec. 5.3). This ALE is calculated averaging the 'age of death' plus the previous ALE. The initial ALE assigned to agents is 100.

The simulation is divided into three periods that have a fixed length and that will be repeated until exhausting the number of initially defined time steps: the **Exchange Period** (when agents exchange norms) , the **Execution Period** (when agents use such norms) and the **Evaluation Period** (when agents evaluate norms). The simulation runs through each of the periods iteratively and repeatedly for the number of time steps defined, except at the beginning of the simulation where the Exchange and Evaluation Period are omitted due to the lack of information to perform those tasks. Nevertheless, the periods are explained in the order they will normally be executed.

5.1 Exchange Period

The **Exchange Period** is executed for 10 time steps and is the period where agents exchange their sets of norms. At every time step, the simulation platform evaluates (following a continuous uniform probability distribution) if an agents has to meet another agent by observing the agent *Interaction Probability*, that is defined as: P_{int} *(Interaction Probability)* $\in [0, 1]$ and specifies the probability of an agent to meet any other agent connected to it. During this period, when two agents meet, they can exchange their sets of social norms using the following *communication protocol*:

1. Agent A meets agent B.
2. Agent A sends a message with structure *M* = {A's Norms, A's Norms Utility, Certificate}; *A's Norms* is the actual set of social norms of agent A, *A's Norms Utility* is agent A's ALE obtained by using that set of norms, and finally, *Certificate* is a boolean value specifying if that message was certified by a *visionary* agent (only visionaries can issue certificates but everyone can transmit them). As it is explained in section 6.4, a *visionary* agent is an agent that is able to make an approximate evaluation of a set of norms before trying it in the real scenario and issue a certificate of that evaluation.
3. Agent B receives the message and analyzes the information received. If A's Norms Utility is higher that its own, it will accept the new norms, otherwise, it will reject them.
4. After the reasoning process, agent B sends a message to agent A informing about the acceptance or rejection of the set of norms.
5. Finally, agent A receives the notification from agent B. If agent B is a *visionary* and it decides to accept the norms, agent A will add in its messages agent B's certificate.

The basic version of the Norm Acceptance Reasoning Process (to be extended in each experiment) that agents use is the following: when agent B receives a message from agent A containing A's norms, agent B will accept if A's utility is greater than its own, otherwise, it will reject agent A's norms . The mechanisms to be studied in the experiment section will refine this process, in order to obtain better decisions. Consequently, the final version agents are donated with is the following:

A If Agent B is not a Liar (explained in section 6.2) and Agent A is not included in Agent's B black list (explained in section 6.3), then Agent B observes if the A's Norms promised Average Life Expectancy is higher than its own norms. If so, Agent B adopts A's norms, saving previously its own norms.

B If Agent B is a *visionary* (explained in section 6.4), it loads a mental simulation with Agent's A Norms and obtains some simulation results. If the mental simulation proves that Agent's A norms are better than Agent's B norms, Agent B adopts them and sends a message to Agent A informing about its adoption as well as the fact it is a *visionary*. Otherwise, if the mental simulation proves that Agent's A norms are worse than Agent's B norms, then agent B rejects them.

C If Agent B is a Liar, or Agent A is included in Agent's B black list, or Agent's B Norms are the same as Agent's A Norms, then Agent B rejects the norms of Agent A. In our experiments, the liar agents are always loaded with a bad set of norms and we do not want them to change to a better one so they introduce instability. This is the reason why a Liar will always reject the norms coming from another agent.

After exchanging norms, agents need to try them out in order to evaluate the efficiency of the new set of norms obtained, in case they accepted new norms. The norms agents have internalized during the Exchange Period are used on the Execution Period.

5.2 Execution Period

Throughout the **Execution Period**, in each time step, our algorithm evaluates firstly (following a continuous uniform probability distribution) if each of the agents have to find resources by observing the agent *Resource Gathering Probability*, that is defined as: P_{rg} *(Resource Gathering Probability)* $\in [0, 1]$ and specifies the probability an agent has to find resources each time step. In case the algorithm evaluates that an agent has to find resources, the agent receives a large amount of resources, that can either use for its own consumption or for donating.

Secondly, in each time step, our algorithm evaluates if an agent has to meet another agent by observing the agent *Interaction Probability* that was previously defined. In the event that the algorithm evaluates positively that an agent has to meet another one, it randomly chooses another agent from the agent's neighbours network. The interactions among agents are done always in pairs, and both agents have to choose an action when interacting. This decision is taken following the *set of social norms* that each agent has internalized. The set of norms in this scenario specifies if the agent has to give or not to give resources to the other agent, depending on both agent's resource level. Following the formalization presented in section 4, in our scenario the set of observables is formed by the following propositional terms: $O = \{$ *Plenty(Me)*, *Plenty(You)*, *Normal(Me)*, *Normal(You)*, *Starving(Me)*, *Starving(You)*$\}$, where: *Plenty(X)* indicates that *Agent's X* resource level is over 100 units; *Normal(X)* indicates that *Agent's X* resource level is between 25 and 100 units; and *Starving(X)* indicates that *Agent's X* resource level is below 25 units. The values that X can take are *Me* and *You*, representing the acting agent and the opponent agent in the interaction. When two agents meet, each agent is able to observe its own level of resources and its opponent's level. The whole list of possible situations (formed by two observables) in which an agent may find itself can be seen in Table 1. The set of possible actions are $A = \{\text{Give Resources}, \text{Do not Give Resources}\}$. Each agent always abides by the set of social norms that it has internalized. When the social norm indicates to give resources, the agent has to decide the amount of resources it gives. Each agent has been provided with a *Donation Reasoning Process* that allows it to calculate the amount of resources to donate. The Donation Reasoning Process is showed in Fig. 1.

Situation		Action
Starving(Me)	Starving(You)	Give / Not Give
Starving(Me)	Plenty(You)	Give / Not Give
Starving(Me)	Normal(You)	Give / Not Give
Plenty(Me)	Starving(You)	Give / Not Give
Plenty(Me)	Plenty(You)	Give / Not Give
Plenty(Me)	Normal(You)	Give / Not Give
Normal(Me)	Starving(You)	Give / Not Give
Normal(Me)	Plenty(You)	Give / Not Give
Normal(Me)	Normal(You)	Give / Not Give

Table 1. *Situations and Actions. Structure of a set of social norms.*

if $(Age_A \geq ALE_A)$ *and* $(Resources_A \geq PlentyLevel)$ **then**
  $Donation = SharingFactor \times (Resources_A - PlentyLevel)$
else
  $Donation = (1 - SharingFactor)^2 \times Resources_A$
end

Fig. 1. Donation Reasoning Process: Age_A corresponds to how old Agent A is. ALE_A refers to the Average Life Expectancy of Agent A. $Resources_A$ is the amount of resources that Agent A posses at that moment. *PlentyLevel* is the level in which the agent is considered to be plenty. And *SharingFactor* is a factor applied to donate a relative amount of the total. In the experiments studied herein this sharing factor is fixed on a 70%.

In other words, when an agent has more resources than what it needs to increase its average life expectancy, it donates more; when an agent do not have enough resources, it donates a smaller amount. The donation reasoning process has been designed in such a way so that it fulfils the motivation of the scenario we are simulating that was introduced in previous sections.

5.3 Evaluation Period

Once the Execution Period is over, it is turn for the **Evaluation Period**. The execution of this period has a duration of one time step just after the Execution Period. During this period each agent evaluates if the set of norms, that were transmitted to it in the last Exchange Period, is a valuable set to keep. If the set of norms received is not better than the previous one, the agent will recover its previous set of norms. An agent evaluates the set of norms after trying them during the execution period. If, while using a set of norms, an agent obtains a better average life expectancy, it will keep those norms. Otherwise, it will discard them and recover the previous one. Consequently, during the Evaluation Period, an agent compares both sets of norms (actual and previous) and keeps the best.

6 Experiments and Results

In this section we analyze the factors that make that a certain set of social norms becomes the dominant set in a society where initially, individuals were using different sets of social norms.
In our scenario the objective of the society as a whole will be to lengthen the average life expectancy of each individual in a *fair* manner. By *fair* in this context we mean that all members of the society obtain a similar life expectancy.
In a previous work [16] we have performed an exhaustive study of all the possible sets of social norms that can appear in our scenario in order to be able to classify these sets in several groups. This study has been performed on homogeneous societies where every member of the society shares the same set of social norms. From this study we can classify the possible sets of social norms in three groups. A **good** set of norms is one that leads into an homogeneous (every agent is similar to the rest in terms of a performance measure) wealthy society. A **bad** set of norms can be of two different types: a

set that leads into an homogeneous poor society or a set that leads into an extremely heterogeneous society (where the distance between the lowest and the highest performance value is very large). Finally, we have the **average** type, applied to those sets of social norms neither good nor bad. From now on we will refer to good, average or bad agents as agents that use a good, average or bad set of norms respectively.

We have decided to load into the simulation a society with the following characteristics:

– The number of agents loaded in the simulation has been fixed to 90. This amount of agents allow us to approximate the society result to a normal distribution, so that it fulfills the central limit theorem.
– Fully Connected Neighbour Network: every agent is connected to all the other agents in its neighbour network.
– All agents have the same Interaction Probability and it has been fixed to $P_I(Agent_i) = 0.1$. This parameter is fixed to this value to avoid the continuous interactions among agents. A limited number of interactions makes the result of this interaction more important when happening. [1]
– All the agents have the same Resource Gathering Probability, and it has been fixed to ($P_{RG}(Agent_i) = 0.0025$).[1]
– When agents find resources, 250 units of resources are found. This value has been chosen to fulfil the motivations previously presented (when agents find resources, it has to find a large amount of them).[1]

Apart from these parameters, we also have to specify the simulation parameters. All simulations are run for 250000 steps. In each simulation, a different configuration on the proportion of agents holding sets of norms of different qualities is loaded. For each configuration, 20 simulations are run and information about how agents change their set of norms during the simulation is kept.

In the following experiments we use a representative set of social norms from each defined type: good, average and bad. Each agent is initially loaded with one of these sets (depending on the experiment).

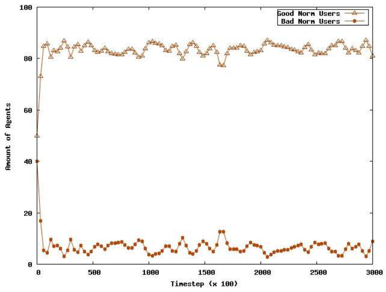
6.1 First Experiment: No Liars, No Image, No Visionaries

An initial scenario is tested with an initial population of sincere agents with up to three different set of social norms (good, average and bad). Different configurations of this scenario has been tested, with different proportions of agents (1 good against 89 bad, and, 10 good against 40 average and 40 bad agents); in all the scenarios the good set of norms becomes the dominant. After simulation, we can conclude that when dealing with a sincere setting, our agents are able to self-organize and reconfigure themselves to use the best set of norms. Therefore, **H1 - When dealing with a sincere population, agents converge to the optimal set of norms** is confirmed.

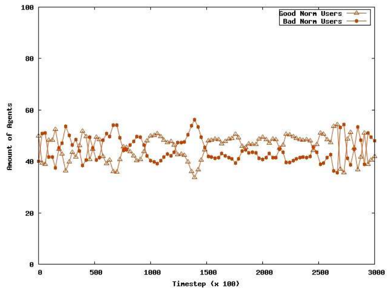
6.2 Second Experiment: Liars Present, No Image, No Visionaries

At this point **liar agents are introduced**. A liar agent lies when informing about the effectiveness of its ethic code (set of social norms). A liar always exaggerates the real

[1] This value has been chosen to fulfil the reference scenario previously presented and obtained from [14].



(a) One Liar



(b) Five Liars

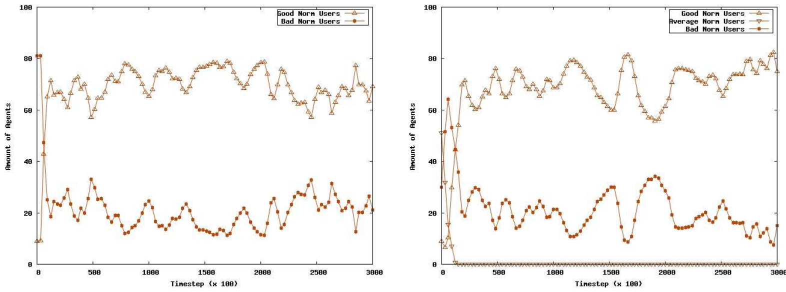
Fig. 2. Liars Present and Image System Off

effectiveness of its ethic code by appliying a positive multiplying factor (that in our experiments has been fixed to 5) to the real value. A non liar agent will always communicate (what it thinks to be) the real effectiveness of its ethic code.
We want to observe the effects of liar agents in the results when our agents do not have any mechanism to recognize them. Two scenarios are studied, although with the same configuration of 50 good agents against 40 bad agents: a first one with just one liar agent, and, a second one with 5 liars agents present. Liar agents are initially loaded with the bad set of norms, for the purpose of introducing instability in the society.

On Fig. 2(a) and Fig. 2(b) we observe that the presence of liars in the simulation introduces a huge instability into the system. We can observe that when the number of liars is higher (Fig. 2(b)), so it is the instability. This instability in real life is solved by introducing several mechanisms to detect liars. One of the mechanisms studied is image. Experimental results partially confirm **H2 - When dealing with a non sincere population, agents need a social evaluation mechanism to converge to the optimal set of norms**.

6.3 Third Experiment: Liars Present, Image, No Visionaries

Image is one of the mechanisms used in several communities when members are interested in detecting frauds. In our experimental settings we have opted for studying image and see how it helps in our stability problem when liars are present.
We donate agents with a Black List structure in order to control interactions with other agents. The black list contains the identities of the agents to be avoided in future interactions. The black list is modified according to the interaction with the other agents and works as follows: agent A will add agent B to its black list if after accepting agent's B norms with a promise of certain life expectancy it has not reached a percentage of that life expectancy. For the experiments performed in this article, this tolerance percentage has been fixed to 80%, and the time before evaluation depends on the promised life expectancy. Agent A will use the minimum amount of Execution Periods to check the veracity of agent's B statement. E.g. if agent B promised 347 steps of survival, agent A will wait: 199 steps (Execution Period) + 1 step (Evaluation Period) + 10 steps (Exchange Period) + 199 steps(Execution Period) = 409 steps before evaluating.



(a) 9 Good VS 81 Bad (b) 9 Good VS 30 Bad VS 51 Average

Fig. 3. Five Liars Present and Image System On

In this experiment, agents are provided with this social evaluation mechanism, and we expect that it helps them in the task of detecting liar agents, reducing thus the instability. After observing in the second experiment that five liar agents were enough to introduce instability into the system, we will reuse that scenario, but this time **agents will use the image system** .

In a first scenario (Fig 3(a)), the simulation is initially loaded with a clear minority of good agents with respect to the bad ones (9 good against 81 bad) where 5 of the bad agents are liars. We observe that after some steps the amount of bad agents is reduced drastically, meaning that agents are detecting liars. In the second scenario (Fig. 3(b)), where the simulation is loaded initially with 9 good agents, 30 bad agents (in which 5 of them are liars) and 51 average agents, results obtained are similar to the first scenario, and again the good set of norms becomes the dominant. Therefore, **H2 - When dealing with a non sincere population, agents need a social evaluation mechanism to converge to the optimal set of norms** is confirmed.

In these previous scenarios, the use of bad norms is reduced but not eliminated. This is due to the simplicity of our image system: it provides satisfying results detecting liars, although it detects some false positives, classifying some agents as liars when they are not. A more complex reputation mechanism would solve this problem.

6.4 Fourth Experiment: Liars and Visionaries Present, Image

A visionary agent is a special kind of agent that is able to build a mental simulation of a society where every member shares the same set of social norms. This set of social norms is any that the visionary agent needs to evaluate. As a result of performing this mental simulation the visionary agent will get a perception about the goodness of that ethic code. After that, the visionary agent informs about the results of the mental simulation to whoever needs it, providing also a certificate. It has to be clear that the mental simulation is performed over a fixed world (both in size and number of agents) and assuming ideal conditions (all the agents share the same ethic code) so it is only an approximation. When visionaries are present, agents have a certain and concise way to see which set of social norms can be the optimal, and therefore, accelerating the process of dominance of the good set over the others. In this experiment we will reuse the scenarios designed previously (with five liars agents, image system available to the agents) and **adding one visionary agent**. In this scenario, the simulation platform is loaded with 50 good agents and 40 bad agents. One of the good agents is a visionary agent and 5 of the bad agents are liars.

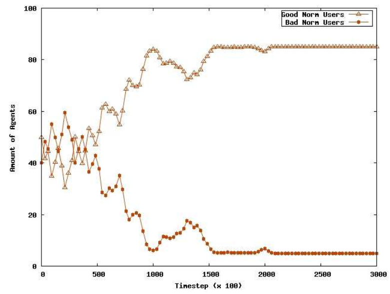


Fig. 4. *Five Liars Present and Image System On. One Visionary Agent*

We can observe in Fig. 4 that the visionary agent provides stability and all the sincere agents end converging into the good set of norms, confirming **H3 - Visionaries accelerate the process of convergence**. The only ones that remain with the bad set of norms are the liars because our design does not allow them to change the set of social norms.

7 Conclusions and Future Work

In this article we have presented a simulated society that has been used to study the process of norm support. Special attention has been paid to image as a mechanism that ensures the correct process of norm support when insincere agents are present. Image is an appropriate way to help a society detect the liars and ignore the information provided by them which introduces huge instability into the system. In addition to the image system, the Visionary mechanism has been presented. This mechanism allows the agents to foresee the effects of suggested changes in the simulated society by launching internal simulations. We can conclude that an image system together with the visionaries' capacity is a good combination for norm support in self-* systems.

All the techniques applied in this kind of simulated self-organized society can be directly translated to real-world applications. One of these applications are the open peer-to-peer information exchange systems. Social norms can help ensuring the equality of all the members, stabilizing in the most efficient set of norms, and detecting fraudulent agents. As part of the future work, after proving that the Norm Support Process is improved by the addition of a reputation mechanism, we plan to apply the same mechanisms into a peer-to-peer information exchange system. Our long-term objective is the implementation of a fair, balanced, trusted and self-organized peer-to-peer network, through the usage of social norms, reputation theory and agent-based simulation.

As another long-term objective, our research will serve as a simulation platform where to confirm some hypotheses in the archaelogical field about how *'the Yámanas'* self-organized and what mechanisms they used.

8 Acknowledgments

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