Understanding social behavior evolutions through agent-based modeling

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Abstract— **Agent-based social simulation as a computational approach to social simulation has been largely used to explore social phenomena. The purpose of this paper is to describe a theoretical model of transmission and evolution of social behaviors in a network of artificial societies (artificial world) using agent-based modeling technology. In this model, each agent (society) is subdivided into social behaviors where individual and social learning occur. The agent-agent interactions are carried out by their social behaviors; otherwise the agent-environment interactions through consumption of ecological resources by its social behaviors in repression and satisfaction.**

We distinguish social behaviors by their repressive capacity and their technical satisfaction. Preliminary results of the model generate several evolutions, but we will focus on the two most important types: firstly, evolutions where the system (all living-agents) will end in a state of "globalization"; i.e. where one social behavior predominates the entire system; secondly, evolutions where an Ecological Hecatomb takes place during the globalization with the repressive social behavior. The model is implemented in java language; its simulation can help to understand the implied processes in humanity's evolution and their trajectories.

Keywords- Agent-based modeling; Social Behaviors; Probabilistic Learning; Repression; Satisfaction

I. INTRODUCTION

Modeling and simulation of soft systems where the human factor is crucial to the system behavior is a difficult and risky task. The models can hardly be validated, unless we have sufficient historical data. Even if we can prove that the model behavior for the past data is correct, this does not mean that it will be valid for the future trajectories. So, it is a common practice to use invalid models of soft systems (in fact, the authors of such models normally do not care about the model validity). This does not mean that the model, even if it is invalid, cannot provide relevant and interesting information. What we should take into account is that the numeric results can be false. The model user must be aware of this, and rather look for behavioral properties that repeat for different data sets and model parameters, using his experience in intuition [13].

In previous works ([11],[12]) Pla-López has built a model of social evolution from a General Theory of Learning [12]. In his model, the environment in where the subsystems (societies) evolve is one-dimensional.

This model was adapted by Nemiche and Pla-López to simulate the duality between orient and occident; introducing a differentiation between individualist and gregarious social behaviors ([8]-[10]). In this work we propose a new version of the model reformulated in terms of agent-based technology. The environment in this version is two-dimensional and the agents are mobile.

The agent-based simulation has demonstrated that it is a tremendous tool for modeling complex systems and especially social systems ([1], [3] - [5]). In this type of simulation the global behavior of a system is the result of individual behaviors and its interactions.

Certainly, one of the key points of the multi-agent simulation is the concept of emergence. This implies that the emergent phenomena are macroscopic models resulting from decentralized interactions of simple individual components [6]. In social science the idea of emergence takes a supplementary dimension due to the importance of complexity [7].

II. THE MODEL

Our model consists of a set of N autonomous and adaptive agents/societies that consume resources in a common environment by satisfaction and repression to achieve their objectives.

Each agent A represents an artificial society; its state is defined by three variables [9]:

1. The dimension m_A of the agent $m_A \in \{1,2,\ldots,m_{max}\}$: in the instant $t=0$ all the agents start with the same dimension 1 (primitive society); this dimension

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increases with time under certain conditions until a maximum value m_{max} in an autonomous way for each agent. With the increase of the dimension we simulate the technological development (progress) for each agent.

2. A vector U of m_A binary components (presence or absence of social behavior code) $U=(U_{mA-1},\ldots,U_1,U_0)$ represents an available social behavior for A. The number of social behaviors available for the agent A is 2^{mA}.
3. $P^t_A(U)$ the weight which specifies the relative importance of the social behavior U of the agent A in the instant t; this weight is expressed by a function of probability ($P^t_A(U)$) which is updated in each step.

Suppose that at time t the dimension of the agent A is 4; in this case the social behaviors available for A are: *(0,0,0,0), (0,0,0,1), (0,0,1,0), (0,0,1,1), (0,1,0,0), (0,1,0,1), (0,1,1,0), (0,1,1,1), (1,0,0,0), (1,0,0,1), (1,0,1,0), (1,0,1,1), (1,1,0,0), (1,1,01), (1,1,1,0), (1,1,1,1)* (binary representation (base 2)). In the simulation interface we represent the social behaviors with its hexadecimal form (base 16); i.e. *1, 2, 3, 4, 5, 6, 7, 8, 9, A, B, C, D, E, F* (example $((1,1,1,1)_2=(F)_{16})$. In each instant t, each social behavior V of an agent A calculates its probability $(\sum_V P^t_A(V)=1)$. We say that a social behavior V predominate in the agent A at the instant t if $P^t_A(V)\geq 0.5$.

A. The Environment Sub-Model

The environment in which the agents evolve is a discrete-space in the form of a two-dimensional grid of cells each having variable and limited quantity of resources.

- $X\in N^*$ and $Y\in N^*$ are respectively the abscissa and ordinate. Each cell is located by its coordinates (x, y) with $x \in [0,X-1]$ and $y\in [0,Y-1]$.
- In this model we use the Euclidean distance; the origin of the grid is located down left.

Each cell is characterized by its initial capacity of resources, its maximal capacity, its rate of regeneration, and a state variable which represents the actual quantity of available resources.

More formally, we use the following notations:

- $K^0(x,y)\in R^+$: the initial capacity ($t=0$) of the cell (x,y).
- $K_{max}\in R^+$: maximal capacity of the cell (x,y).
- $\rho \in]0,1[$: the rate of regeneration of the cell (x,y).
- $K^t(x,y)\in R^+$, with $K^t(x,y)\leq K_{max}$: the quantity of resources at the instant t.

  When an agent occupies the cell (x,y) (in this model a cell (x,y) only can be occupied by one agent at the instant t), the value $K(x,y)$ is updated as:

$$K^{t+1}(x,y)=min[K^t(x,y)+\rho.K^t(x,y)-(CS^t+CR^t),K_{max}]$$

where CS is the consumption of the resources in satisfaction by the agent A.

CR is the consumption of the resources in repression by the agent A.

The formulas of CS and CR are presented in Section K.

When the cell is free, the value of $K(x,y)$ increases under the following formula:

$$K^{t+1}(x,y) =min[K^t (x,y) +\rho K^t (x,y), K_{max}]$$

The initial resource capacity of the cells are randomly distributed between two values K_{min} and K_{max} (in this version K_{min} and K_{max} are constant parameters of the model for all the cells).

B. Static Social Behavior Proprieties

The social behaviors in this model are characterized by their initial repressive capacity and their technical possibility of satisfaction. The initial repressive capacity of a social behavior depends on its might $\mu(U)$ and its ferocity $\nu(U)$. We want the initial repressive capacity of a social behavior to be null when its might or its ferocity is null. The simple formula is the product [9]; i.e. $RC(U)= \mu(U).\nu(U)$

Which guarantees that $RC(U)=0$ if $\mu(U)=0$ or $\nu(U)=0$

1) The might: we want the might of a social behavior U of an agent A to increase with the dimension of U and with the included attributes; in a way that a social behavior with a great dimension possessus a great might. Taking into consideration the binary representation of social behavior, the simple function that satisfies these conditions is the decimal representation of the social behavior [9] ; i.e. $\mu(U)=\sum_i 2^i U_i$

2) The ferocity: we assume that the ferocity decreases in the social behaviors that are more advanced (social behavior U with $U_{mmax-1}=1$), and increases in the social behaviors that are less advanced $(U_{mmax-1}=0)$.

The formula of the ferocity in this model is:

$$\nu(U) = 1-(\frac{2.\sum_i 2^i U_i}{2^{m_{\max}}-1}-1)^2$$

We want the initial repressive capacity of the social behavior (0,1,…,1,1) to be equal to 1. For this we have to divide the might by $2^{mmax-1}-1$. The new formula of the might is:

$$\mu(U)=\frac{\sum_{i=0}^{\max-1} 2^i U_i}{2^{m_{\max}-1}-1}$$

3) Technical possibility of satisfaction: we hope that the satisfaction increases with the technical progress between the values 0 and 1. Thus, the simple formula is:

$$\pi(U)=\frac{1}{m_{\max}}\sum_{i=0}^{m_{\max}-1} U_i$$

U	μ(U)	ν(U)	RC(U)	π(u)
U=0	0	0,3	0	0
U=1	0,143	0,461	0,066	0,25
U=2	0,286	0,61	0,174	0,25
U=3	0,429	0,741	0,318	0,5
U=4	0,571	0,85	0,486	0,25
U=5	0,714	0,932	0,665	0,5
U=6	0,857	0,983	0,842	0,5
U=7	1	1	1	0,75
U=8	1,143	0,982	1,122	0,25
U=9	1,286	0,929	1,194	0,5
U=A	1,429	0,84	1,2	0,5
U=B	1,571	0,719	1,129	0,75
U=C	1,714	0,568	0,974	0,5
U=D	1,857	0,394	0,732	0,75
U=E	2	0,202	0,404	0,75
U=F	2,143	0	0	1

Table I
The values of the static social behavior proprieties with m=4

C. Multi-agent Learning

We use the probabilistic learning model build by Pla-López [12]. This model is based on the law of positive and negative reinforcement which permit the agents to update their proper knowledge bases by adding or deleting information from the perception of positive and negative effects of their actions.
The function of the fulfillment of the goal $PG_A(U)$ of a social behavior U of the agent A will depend on the technical possibility of satisfaction $\pi(U)$ and a factor $(1-\sigma_A(U))$ determined by the social context [9]:

$$PG_A(U) = \pi(U)(1-\sigma_A(U))$$

$\sigma_A(U)$ is the suffered social repression of the social behavior U in the agent A.

The probability $P_A(U)$ of the social behavior U of an agent A increases when the goal is accomplished; in way that, a value of $PG_A(U)$ superior to a reference value PR_A determines an increase of the memory accumulator function $f_A(U)$:

$$\begin{cases} f_A^{t+1}(U) = \max\left\{f_A^{t}(U) + \lambda_i \left(PG'_A(U) - PR'_A\right)P_i^t(U), 0\right\} \\ f_A^{0}(U) = K_A^t \quad si \;\; U \le 2^{m_A} - 1 \;\; y \;\; f_A^{0}(U) = 0 \; si \, U > 2^{m_A} - 1 \end{cases}$$

$$p_A^t(U) = \frac{f_A^t(U)}{\sum_V f_A^t(V) = B_A^t} \quad \textit{is calculated only if } B_A^t \neq 0$$

$$PR'_A = \sum_V PG'_A(V)\, p'_A(V)$$

K_A^t is the capacity of resource of the cell occupied by the agent A.

In this formula of the memory accumulator function $f_A(U)$, the learning of a social behavior depends only on the individual learning without considering the social learning.

D. Technological Progress

We simulate the technological development (progress) of an agent A with the increase of its dimension m_A. This increase has two causes that react additionally [9]:

1. The probability of the increasing dimension increases linearly with the accumulated memory of the agent A; expressed by B_A in the way that if $B_A \geq prg$ then the dimension of the agent A increases with one unity (prg is parameter of the model).
2. The dimension may increase by technological diffusion; which we express by the accumulation of information from other agents with dimensions superior to the dimension of the agent A.

Thus, *the* dimension of an agent A increases when the following condition is accomplished:

$$\beta + \sum_{U > 2^{m_A} - 1} P_A^t(U) + \frac{B_A^t}{prg} \ge 1$$

Where β is a uniform random variable in the interval]0,1[.

E. Reproduction, death of agents

In this model an agent A may die by two causes [9]:

1. By dissatisfaction: when B_A=0 ; i.e. $f_A(U)=0$ for each U. An agent can arrive to this state when none of its social behaviors leads to the complement of the goal.
2. By natural death: this happens with high probability when the influence of the learning of the agent A on its behavior is of less importance. This occurs when B_A approaches a maximum value called *tanatos* (parameter of the model).

The reproduction of the agents is produced by two ways [9]:

1. By relay: when an agent dies naturally, the relay is immediately produced with the appearance of a new agent "neophytes" which occupies the cell freed due to a natural death. If we introduce a random variable $\alpha_1 \in]0,1[$, we can express the condition of the relay by:
$$\alpha_1 + \frac{B_A^t}{tanatos} \ge 1$$
2. By recuperation: when a new neophyte agent occupies a cell freed due to a dissatisfaction death. Among these cells freed, we would facilitate the recuperation of the cells previously predominated by less evolved social behaviors. If we introduce a random variable $\alpha_2 \in]0,1[$, we can express the condition of the recuperation by:
$$\alpha_2 + \sum_U a(U) P_i(U) \ge 1$$

Where $a(U) = a_0\left(1 - \frac{2U}{2^{m_{\max}} - 1}\right)$, $a_0>0$ and $U=\sum 2^i U_i$

When the recuperation or the relay is produced, the memory accumulator function of the new neophyte agent is initialized by:

$$f_B^t(U) = K_B^t \quad \forall\, U \le 2^{m_B} - 1$$

$$f_B^t(U) = 0 \quad \forall\, U > 2^{m_B} - 1$$

Where K_B is the resource of the cell occupied by the agent *B*,

m_B is the dimension of the new neophyte agent *B*.

In the case of the relay, the dimension m_B of the neophyte agent is equal to that of the dead agent. Nevertheless, in case of the recuperation, dimension m_B of the neophyte agent is equal to the maximal dimension of its nearest neighbors.

F. Agents' social Impact

The social impact (influence) of an agent *A* on another agent *B* is expressed by the following formula:

$$IMP(A,B) = \sum_U P_A(U) impact(U, d(A,B))$$

Where *d(A,B)* is Euclidean distance between agent *A* and agent de *B*,

impact(U,d(A,B)) is the social impact of the social behavior *U* at the distance *d(A,B)* [11:

$$impact(U,d) = mimp(U) + \max(0, \frac{d_\mu - d}{d_\mu})\left(Mimp(U) - mimp(U)\right)$$

$$d_\mu = \min(1, \mu(U)) d_{\max};$$

$$mimp(U) = \max\left(0, \frac{\mu(U)-1}{\mu_{\max}-1}\right);$$

$$Mimp(U) = \frac{2 - mimp(U)}{\min(1, \mu(U))}$$

d_{max} is the maximal distance between two cells in the grid.

G. Social neighboring

The social neighbors of an agent *A,* according to the model are the set V_A of agents that socially impact (affect) the agent *A*:

$$V_A = \{\text{Agent } B \,/\, IMP(B,A) \ne 0 \text{ and } B \ne A\}$$

H. Communication between agents

The formulation of the multi-agent probabilistic learning model considers only the individual learning; i.e. the agents learn only from their own experiences. So that the agents can also learn from the experiences of their social neighbors (social learning), we have replaced the individual learning rate $P_A(U)$ of a social behavior U of an agent A by the learning rate $PL_A(U)$ [9] expressed by:

$$PL_A(U) = P_A(U) + REC_A\left(\sum_{B \in V_A} EM_B P_B(U) impact(U, d(B,A))\right)$$

where

$$REC_A\left(\sum_{B \in V_A} EM_B P_B(U) impact(U, d(B,A))\right)$$

is the social learning rate,

$P_A(U)$ is the individual learning rate.

REC_A, *EM_A* are respectively the reception capacity and the emission capacity of an agent *A*.

$$REC_A = \sum_V P(V) rec(V)$$
$$EM_A = \sum_V P(V) em(V)$$
$$em(V) = rec(V) = \mu(V)/2$$

The new formulation of the learning that integrates the individual and social learning is:

$$\begin{cases} f_A^{t+1}(U) = \max\left\{f_A^t(U) + \lambda_i \left(PG_A^t(U) - PR_A^t\right) PL_i^t(U), 0\right\} \\ f_A^0(U) = K_A^t \quad si \;\; U \le 2^{m_A} - 1 \;\; y \;\; f_A^0(U) = 0 \; si \; U > 2^{m_A} - 1 \end{cases}$$

$$p_A^t(U) = \frac{f_A^t(U)}{\sum_V f_A^t(V) = B_A^t} \quad is\ calculated\ only\ if \;\; B_A^t \ne 0$$

I. Resignation

In our model, the function of the fulfillment of the goal *$PG_A(U)$* of a social behavior *U* is compared with the local reference *$PR_A(U)$* expressed by the pondered average:

$$PR_A^t = \sum_V \dot{P}G_A^t(V) p_A^t(V)$$

We have modified the reference function *$PR_A(U)$* of the social behavior *U* in the agent *A* to be a reference that considers the social neighboring of the agent *A* (for that, we replace the learning individual rate *$P_A(U)$* by the learning rate *$PL_A(U)$*) :

$$PGM_A^t = \frac{\sum_V PG_A^t(V) PL_A^t(V)}{\sum_V PL_A^t(V)}$$

In the practice, the resignation is produce with delay *Tr*. Thus, this we subtract from the function of the fulfillment of the goal *PG_A* the value *PR* that evolves linearly toward the average satisfaction *PGM*

$$\begin{cases} PR_A^{t+\Delta t}(U) = PR_A^t(U) + \frac{\Delta t}{Tr_A}\left(PGM_A^t - PR_A^t\right) \\ PR_A^0(U) = \sum_{U < 2^{m_{\max}} - 1} \frac{\pi(U)}{2^{m_{\max}}} \end{cases}$$

We want to model a situation where the resignation is slower when the ferocity is greater, for this we consider:

$$Tr_A = \Delta t . Kr\left(\sum_U P_A^t(U) . \nu(U) + 1\right)$$

Kr is a constant parameter.

J. Repressive Adaptation

Remember that the function of the fulfillment of the goal of a social behavior *U* in the agent *A* is:

$$PG_A(U) = \pi(U)\left(1 - \sigma_A(U)\right)$$

This function increases with the increase of the technical possibility of satisfaction $\pi(U)$ and decreases with the increase of the suffered social repression ($\sigma_A(U)$) of the social behavior U.

Note that $V_A^+ = V_A \cup \{A\}$, is the set of the social neighboring of the agent A including the agent itself. In this model each social behavior U in the agent A represses the other social behaviors different than itself in the set V_A^+. So that the agents can survive they must adapt to the suffered social repression, by producing in return a social repression (repressive capacity). The suffered social repression of a social behavior U of an agent A depends on the weight (probability) of the social behaviors V different to U in the agents of the set V_A^+; of the social impact of the agents of the set V_A^+ on the agent A ; and repressive capacity of these social behaviors [9] :

$$\sigma_A(U) = \frac{1}{S}\sum_{V \neq U}\sum_{B \in V_i^+}\left(p_B(V)\right)^2 sts_B(V) impact\left(V, d(B, A)\right)$$

Where $sts_B(V)$ is the repressive capacity of the social behavior V of the agent B,

S is number of the living agents.

The repressive capacity of a social behavior U of the agent A evolve from the initial repressive capacity $RC(U)$ to the suffered repression by the social behavior U in the agent A with a delay T_A :

$$sts_A^{t+\Delta t}(U) = sts_A^t(U) + \frac{\Delta t}{T_A}\left(\sigma_A^t(U) - sts_A^t(U)\right)$$

$$sts_A^0(U) = RC(U)$$

We want to model a more rapid adaptation to the suffered repression, when the agent has more advanced technology (the most advanced technology is reflected by high values of the might):

$$T_A = \Delta t . K_a \frac{\mu_{\max}}{\sum_V \mu(V) P_A(V)}$$

Where μ_{max} is the maximal might ($\mu_{max} = \mu(1,1,...,1,1)$), and K_a is a parameter of the model.

K. Consumption of resources

The interactions of the agents with their environment through its social behaviors affect the technical possibility of satisfaction:

$$\pi_A^t(U) = \pi(U) . \frac{k_A^t}{K_{\max}}$$

So, the new formulation of the function of fulfillment of the goal is:

$$PG_A^t(U) = \pi_A^t(U)\left(1 - \sigma_A^t(U)\right)$$

The agents consume the resources by satisfaction and repression.

The quantity consumed by satisfaction is $CS_A^t = \sum_U p_A^t(U)\pi_A^t(U)$, and the quantity consumed by repression is $CR_A^t = \sum_U p_A^t(U) sts_A^t(U)$.

Some generated social evolutions of the model end in the Ecological Hecatomb state; i.e. the end of the social evolution due to the exhaustion of the resources (death of all agents).

III. PRELIMINARY RESULTS

With our probabilistic model we have obtained several types of social evolutions. In this work, we focused only on the following social evolutions:

- Evolutions where the system (all the agents) ends predominated by the same repressive social behavior $U=(0,1,...,1,1)$; i.e. repressive globalization state. The perpetuity of the capitalist globalization according to Fukuyama [2] can be a possible interpretation of this result (see figure 1 in the annex).
- Evolutions where the repressive globalization is overcome by another free scientific globalization $U=(1,1,...,1,1)$, characterized by a great satisfaction and without initial repressive capacity (see figure 2 in the annex).
- Evolutions where the system ends with Ecological Hecatomb; i.e. death of all the agents due to exhaustion of resources (see figure 2 in the annex).

The values of the initial parameters used in these simulations are: $ka=70$; $prg=10000$; $\Delta T=100$; $Tanatos=20000$; $Tmax=20000$; $K_{max}=30$; $\rho= 0.03$; $X=10$; $Y=10$, the number of agents is 90.

IV. CONCLUSIONS, DISCUSSIONS ET PERSPECTIVES

The presented simulation is a first stage of research that should be continued with sensitivity analysis. Perhaps similar models can be developed using the System Dynamics approach, with a more global view. But, by using System Dynamics we will not be able to see the agents' movements.

The simulation of this model can help to understand:

- The process implied in the social evolution of humanity and its possible trajectories.
- The conditions that favor the perpetuity of the repressive globalization (capitalist globalization).
- The conditions that favor the possibility of overcoming the repressive globalization by another free scientific globalization; based on the satisfaction instead of the repression.
- The conditions that favor the Ecological Hecatomb.

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ANNEX

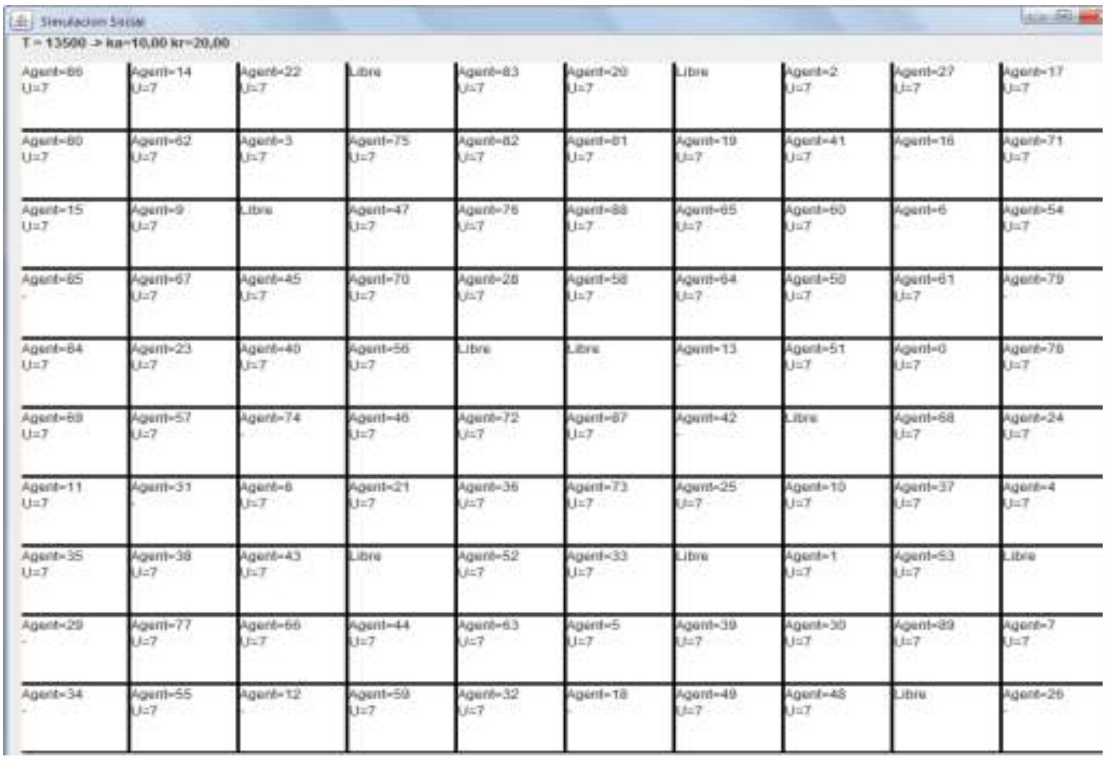

Figure 1. Example of an evolution that ends with the perpetuity of repressive globalization (U=7)

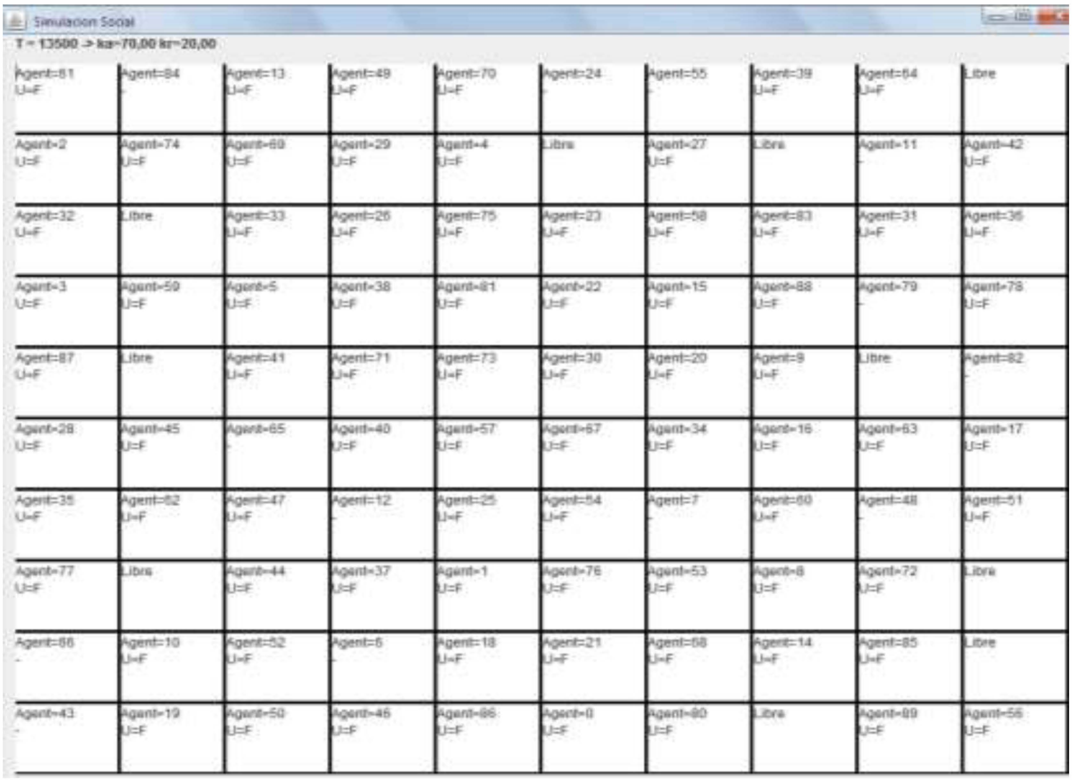

Figure 2. Example of an evolution that ends with a free scientific globalization (U=F)

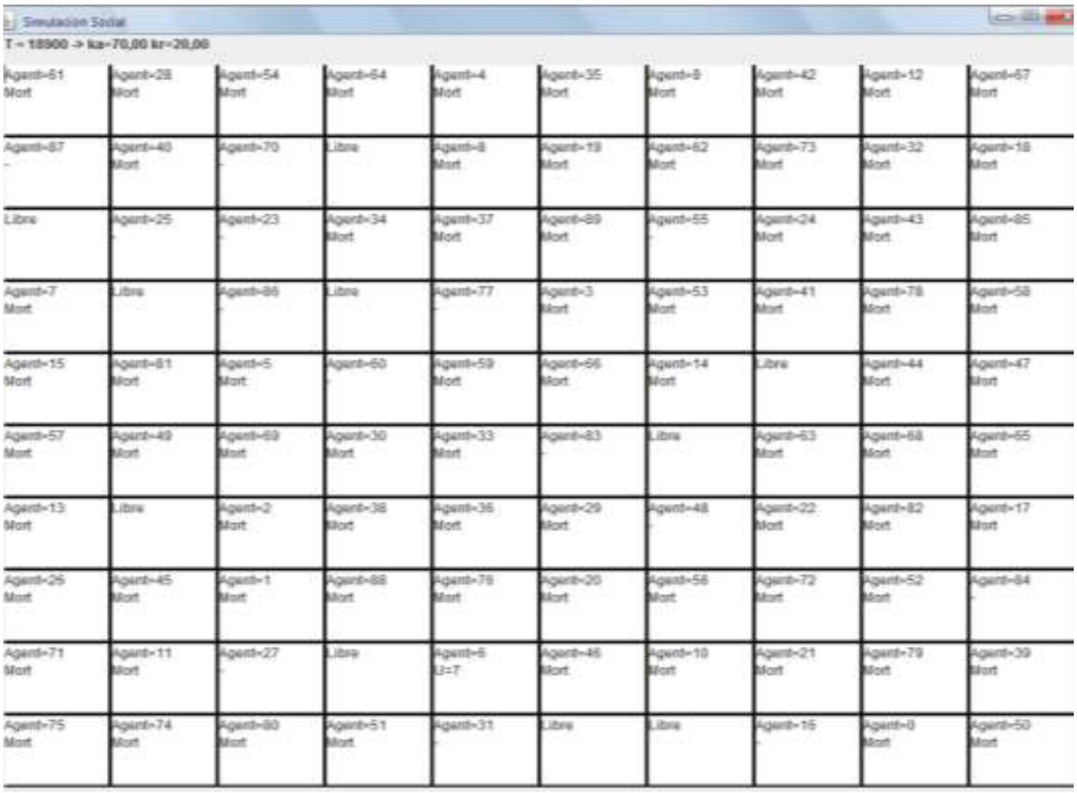

Fig. 3 Example of an evolution that ends with Ecological Hecatomb (Mort=Dead)