A Theoretical Agent-Based Model to Simulate the Rise of Complex Societies

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Abstract Nowadays, societies consist of hundreds of millions of people governed by one political system, and cooperation between individuals transcends face-to-face cooperation. However, in early history, groups of people did not exceed hundreds of individuals, and cooperation existed at low levels. So how did human societies evolve from small groups known by face and name into the huge anonymous groups of today? Our model tries to answer this question based on Freud's hypothesis stating that civilization could not arise and evolve without the repression of satisfaction (repression of human desires). In social evolution the repression of satisfaction can be interpreted as the repression of competition between society members the thing that increases the society power and helps on the formation of complex societies. In order to test this hypothesis we implemented an agent-based model where a large number of primitive societies are distributed in a grid of cells; initially, each cell is an independent polity. In each time step, all border cells (cells having at least one neighbor of a different polity) have a chance to start an attack and take over one cell from its neighbors. During the simulations we can observe the emergence of complex societies the thing that validates our hypothesis.

Keywords Agent-based modeling · Repression of satisfaction · Cooperation · Competition · Social simulation

1 Introduction

In the present age, the population of the largest countries is more than a billion. The world is full of societies with millions of citizens living in large lands ruled by one political system and maybe even by one person, the thing that was impossible in

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the early ages before agriculture. The emergence of agriculture allowed humans to settle in fertile lands and have a surplus of food, which facilitated the reproduction and growth of primitive groups. According to Turchin, the competition for resources between neighboring groups grew, as well as the attacks of nomadic groups aiming to get agricultural products by force. The competition between agriculturalists and nomads obliged the groups with the same interests to cooperate and defend their welfare. Consequently, the groups neglected their differences and built societies [1].

The evolution of all species is based on the natural selection [2]. However, doesn't natural selection favor competition and selfish behaviors more than cooperation? Then how could humans cooperate and organize huge societies where individuals have no genetic relations? Even with the advantage of selfishness and competition in nature, cooperation behavior has been observed, and many scientists tried to explain it. Cooperation exists at several levels. The first one is cooperation between relatives (kin selection), which is explained as the self-sacrifice for the favor of common genes [3]. The second is the cooperation between members in small groups (face-to-face cooperation), which in turn is explained by the reciprocity, reputation, retribution, and group selection [4–7].

The last level is large-scale cooperation, which is the key factor to the emergence of large-scale societies. Robert Boyed et al. argued that cultural adaptation is the main reason behind the evolution of large-scale cooperation [8]. They based their hypothesis on three assumptions. The first is that humans developed the ability to learn from each other, which created an evolution by cultural accumulation. Therefore, this ability was favored by natural selection because it provided the cultural adaptation needed in their social environment during the rapidly changing climates. The second is that rapid cultural adaptation increased the differences between groups and also increased competition between groups. However, reciprocity and reputation systems can balance selfish and cooperative behaviors within groups. The last assumption is that in culturally evolved cooperative groups, social selection and moral systems favor the reproduction of members with social norms that support pro-social motives; it also punishes the members who violate those norms, making their chances of reproduction very low. Thus, those moral systems forced by punishment and reward favored the success of individuals that functioned well in such an environment and also favored motives like shame, guilt, and other norms that facilitate the rise of large-scale cooperation [8].

In addition to cooperation, repression of competition also has an important role in the rise of large-scale societies. Alexander argued that repression of reproductive competition in human groups, added to the ferocity of competition between outside groups, helped spread human social structures [5, 9, 10]. Those social structures (social norms and social institutions) are the principal key to the emergence of large-scale societies. Frank goes with the same hypothesis and states that the fitness of a group increases with the decrease of competition within it. Low competition maximizes the number of individuals who benefit from resources and prevents the damage caused by overexploitation [10]. However, natural selection does not favor the repression of competition inside groups because individuals try to get maximum resources at the expense of their neighbors to ensure their survival. Besides that, we can observe the evolution of internal repression traits in nature [10–14]. To explain that, Frank proposed a model where individuals have a variable called competition intensity (z) and another variable (a) called mutual policing, which represents the individuals' contribution to the repression of competition within the group. This mutual policing, also called punishment, helps the group reduce the competition and increase the cooperation among group members, and as a result, the group gains higher fitness [10].

The ability of humans to cooperate and live in huge groups without any genetic relations (this ability is called ultrasociality) produces large-scale societies [15]. A theoretical model presented by Turchin et al. [15] suggested that the evolution of ultrasocial norms and institutions is the reason behind the emergence of large-scale societies. As well, those ultrasocial norms and institutions result from intense competition and warfare between societies which depends on the spread intensity of military technology. Turchin used two vectors in his model: the first represents ultrasociality traits responsible for the power of a polity. The second vector is for military technology that is basically responsible for warfare intensity and ethnocide [15].

Another try to explain the huge cultural diversity in the world is the model of Talukdar et al. [16]. They made a computer model in a two-dimensional domain to simulate the interactions between cultures. The main dynamical processes used in their work are inspired by historical rules of expansion, interaction, and merging among cultures, namely growth, assimilation, invasion, aggression, and annihilation. From simple rules to define different interactions between cultures, the model pictured some interesting data in agreement with historical data, such as the intensity of wars in the primitive period compared to the modern one and the appearance of globally polarized cultures [16].

In this work, we propose a theoretical agent-based model to explain how large-scale societies emerged based on Freud's assumption about the emergence of civilization. Freud considers that without the restraint of human desires, civilization could not exist [17]. The central premise of this model is that the repression of individuals' satisfaction within the group that helps have strong societies is the result of the suffered repression caused by the neighboring societies (the risk of an attack from a neighboring group). The outside danger forces the individuals to cooperate and contribute to mutual policing to reduce competition inside the group.

Agent-based modeling (ABM) is a bottom-up approach of social simulation used to facilitate the modulization of social complex phenomenon. One of the main advantages of ABM is its ability to produce macro-scale phenomena (complex patterns) from simple behavioral rules at the micro-scale. It is based on agents who interact with each other and their environment according to simple rules. Agents may be individuals or collective entities that have attributes and methods. While the environment is the place where they live, they exploit it and interact with it according to specific rules. As for the rules, they are simple instructions that organize the interactions between the model elements [18–20].

2 Methods

2.1 General Logic of the Model

In this work, we develop an agent based model to understand how human societies grow from primitive societies where small groups are unified with face-to-face cooperation to complex societies of today. Our study is limited to the Old World, where the conflicts between societies occur only by land. Our simulation takes place on a two-dimensional hexagonal grid of cells. Each cell represents a community (local society). Each community is characterized by a satisfaction vector, a fitness, a power, and a suffered repression. At the start, each community is independent, and has six neighbors.

Satisfaction noted as $\boldsymbol{\pi}^{\boldsymbol{i}}$, is a binary vector with n_{sat} traits $\pi^i(t) = \big(\pi_1^i(t), \ldots, \pi_{n_{sat}}^i(t)\big)$, where $\pi_k^i(t) \in \{0, 1\}, \forall k \in \{0, \ldots, n_{sat}\}$, where n_{sat} is a parameter of the model. The presence of all the satisfaction traits in a polity refers to a primitive society where there is no norms or restrictions to respect.

The satisfaction intensity for an independent polity "i" is calculated as the average value of the satisfaction traits:

$$\overline{\pi}^i(t) = \frac{1}{n_{sat}} \sum_{l=1}^{n_{sat}} \pi_l^i(t) \tag{1}$$

For primitive society $\overline{\pi}^i(t) = 1$.

For multicell polity "i" the satisfaction intensity is defined as:

$$\overline{\Pi}_i(t) = \frac{1}{S_i} \sum_{k=1}^{S_i} \overline{\pi}^k(t) \tag{2}$$

where $\boldsymbol{S_i}$ is the polity size (number of cells of the multicell polity "i"), and $\overline{\pi}^k$ the satisfaction intensity of the individual polity "k" [21].

To calculate the value of the individual fitness of a polity "j" that belongs to a multicell polity "i", we are inspired by Frank's formula [10]:

$$\begin{aligned} w_{ij}(t) = &\left(\overline{a}_i(t) - c \cdot a_{ij}(t) + (1 - \overline{a}_i(t)) \cdot \frac{\overline{\pi}^j(t)}{\overline{\Pi}_i(t)}\right) \\ &\big(1 - (1 - \overline{a}_i(t)) \cdot \overline{\Pi}_i(t)\big)(1 - \overline{\sigma}_i(t)) \end{aligned} \tag{3}$$

where

- $\overline{\sigma}_i(t)$ represents the suffered repression by the multicell polity "i" from its neighbors (social context) [12–14, 22];

- $a_{ij}(t)$ is an individual's participation in mutual policing. Policing is a mechanism that reduces the competition within the group by repressing the satisfaction of individuals. The value of the individual's policing increases with the increase of the suffered repression (external danger); which favors intragroup cooperation and increases the fitness of the group [10];
- $\overline{a}_i(t)$ is the average level of policing in the polity "i";
- $ca_{ij}(t)$ is the cost to live in a group;
- c is a parameter of the model;

For one-cell polities, the fitness is simplified as:

$$w_i(t) = \left(1 - \overline{\pi}^i\right)(1 - \overline{\sigma}_i(t)) \tag{4}$$

According to Freud, repression of individual satisfaction is necessary for technical progress of the group [17]. Which leads to powerful polities and facilitates the rise of complex societies.

The individual policing increases with the increase of suffered repression and the increase of the average satisfaction:

$$a_{ij}(t) = \overline{\pi}^j(t).\overline{\sigma}_i(t) \tag{5}$$

The Suffered Repression $\boldsymbol{\overline{\sigma}_i}(t)$ represents the danger of neighboring societies [12–14, 22]. It is calculated based on their Power:

$$\overline{\sigma}_i(t) = \frac{\sum_{j \in V_i^*}^{j} Power_j(t-1)}{\sum_{j \in V_i}^{j} Power_j(t-1)} \tag{6}$$

V_i^* is the set of neighboring societies of the polity "i" with "i" excluded, V_i is the same neighborhood with polity "i" included. At the start of the model we consider $\overline{\sigma}_i(0) = 0$ for all cells.

Power of a polity "i" is defined as [15]:

$$Power_i(t) = 1 + \beta S_i \overline{w}_i(t) \tag{7}$$

with

$$\overline{w}_i(t) = \frac{1}{S_i} \sum_{j=0}^{S_i} w_{ij}(t) \tag{8}$$

both the size S_i and the average fitness of the polity $\overline{w}_i$ increase the polity's Power, β is the coefficient that translates fitness into polity's power.

We summarize the variables of our model in Table 1:

Table 1 Entities of our model

Entities	Variable name	Possible values
One cell polity "i", it can be a piece of an empire"j", Or An independent polity (local polity "i")	(x, y) coordinates (localization)	([− 27, 27], [− 27, 27])
	Imperial-index	0: for independent polity An integer for polities that belong to an empire {1, … 100,000}
	Satisfaction vector $\boldsymbol{\pi}^{\boldsymbol{i}}$	$\pi^i(t) = \left(\pi_1^i(t), \ldots, \pi_{n_{sat}}^i(t)\right)$, where:$\pi_k^i(t) \in \{0, 1\} \forall k \in \{0, \ldots, n_{sat}\}$
	Satisfaction intensity $\overline{\boldsymbol{\pi}}^{\boldsymbol{i}}$ (average value of satisfaction traits)	[0.1,1]
	Individual fitness $\boldsymbol{w}_{\boldsymbol{ij}}$ Or ($\boldsymbol{w}_{\boldsymbol{i}}$ for independent polity)	[0, 1]
	Power: $Power_i$ calculated for independent polity	[1, 500]
	Suffered repression: $\overline{\boldsymbol{\sigma}}_{\boldsymbol{i}}$ calculated for independent polity	[0, 1]
	Individual policing $\boldsymbol{a}_{\boldsymbol{ij}}$, (null for independent polity)	[0, 1]
Multicell polity (Empire "i")	Imperial-Index	{1, …, 100,000}
	Average satisfaction intensity:$\overline{\Pi}_i$	[0.1, 1]
	Average fitness:$\overline{\boldsymbol{w}}_{\boldsymbol{i}}$	[0, 1]
	Power:$\boldsymbol{Power}_{\boldsymbol{i}}$	[1, 500]
	Suffered repression $\overline{\boldsymbol{\sigma}}_{\boldsymbol{i}}$	[0, 1]
	Average policing $\overline{\boldsymbol{a}}_{\boldsymbol{i}}$	[0, 1]
	Size $\boldsymbol{S}_{\boldsymbol{i}}$	{1, 2, …, 600}
Environment	Grid of hexagonal cells	55 × 55 = 3025 cells

2.2 *Warfare Between Polities*

In this model, conflicts between societies are managed in the same way as in Turchin's model [15]. In each time step, all border cells (cells having at least one neighbor of a different polity) have a chance to start an attack in a random direction. If the attacked cell is from the same polity nothing happens, if not, war can be initiated between two polities with probability P-attack, with P-attack a parameter of the model. The order in which the attacker cells are chosen is randomized every time step [15].

An attack can be successful with probability $P_{success}$ defined as:

$$P_{success}(t) = \frac{Power_{attacker}(t) - Power_{defender}(t)}{Power_{attacker}(t) + Power_{defender}(t)} \tag{9}$$

If $P_{success} < 0$ the attack fails by definition, and nothing happens. If $P_{success} > 0$ the attack is successful, the attacked cell will be annexed to the polity of the attacker. The attacked cell may also copy the satisfaction vector of the attacker, with a probability $P_{ethnocide}$.

2.3 Sociocultural Dynamics: (Mutation, Ethnocide)

The dynamic process of our satisfaction vector is defined by two mechanisms:

- The first one is mutation, it represents random changes in the satisfaction vector [15]. At each time step, for every cell, we chose a random position in satisfaction vector; its value may change from 0 to 1 with a probability μ_{01} if the value of the trait is 0, or from 1 to 0 with probability μ_{10} if the trait value is 1. We note that we made the first position of all satisfaction vectors equal 1, and we don't change them in mutation, so we eliminate the case where $\overline{\Pi}_i(t) = 0$. We assume that gaining a satisfaction trait is much easier than losing it $\mu_{01} \gg \mu_{10}$ because it is easier to break social norms than to respect them and add new ones [15].
- The second mechanism is Ethnocide or (Forced cultural assimilation). After an attack, we calculate a probability [15]:

$$P_{ethnocide}(t) = \varepsilon_{min} + (\varepsilon_{max} - \varepsilon_{min})\big(1 - \overline{\Pi}_{attacker}(t)\big) \tag{10}$$

and the defeated cell may copy the satisfaction vector of the winning cell with probability $P_{ethnocide}$. ε_{min} is the minimum value $P_{ethnocide}$ can have when the average satisfaction is at maximum 1, and ε_{max} is the maximum value when the average satisfaction is near to 0. Here we consider that a society with less satisfaction can have more control over new annexed cells.

2.4 Collapse

Wars cause societies to grow and expand through assimilation, aggression and annihilation. However, they all inevitably decay afterwards because of the repercussions of those wars and the pluralism leading to civil wars, among other factors. In our model we define the probability of collapse as in Turchin model [15]. At each time step, each polity can disintegrate into polities with one cell territory each. The probability of the collapse increases with the polity size S_i and decreases with the average fitness $\overline{w}_i$:

$$p_i(t) = \delta_0 + \delta_1 S_i - \delta_2 \overline{w}_i(t) \tag{11}$$

δ_0, δ_1 and δ_2 are parameters of the model. $\delta_0 = 1/20$ represents the baseline disintegration probability. $\delta_1 = 1/20$, so a polity with low fitness will certainly collapse after size of 19 cells. And finally the δ_2 is defined in a way that every empire that reaches the size 600 will collapse [15].

3 Results and Discussion

The simulation of our model shows, in a two-dimensional grid of cells, the formation, the expansion, and the collapse of many complex societies. The main result of this work is as expected: the decrease of individual satisfaction facilitates the rise of large-scale societies.

From the simulations, we observed that societies appear in the same way across all the chronology of our simulations, where we note the emergence, expansion, and then decline of complex societies. However, the difference lies in the size of the constituent empires as they expand more as time progresses in the model. At the start of the simulation, the formed societies are small with relatively high satisfaction (which translates the absolute individual freedom in primitive societies where there are no norms and laws to organize communal life), afterward as time passes, due to the logic of our model, the societies' satisfaction decreases the thing that refers to the emergence of social norms and institutions that enable human groups to cooperate with each other and live in huge societies.

Here we present images from a simulation as an example to show the general pattern of the simulations.

Every color defines a different society, and the size is the number of cells with the same color.

To test our model, we decide to examine how sensitive our results are according to the variations of the variables: Number of Traits "n_{sat}" of the satisfaction vector, and the cost to live in an Empire "c". For other parameters, we chose fixed values as a start to facilitate our tests.

- Note: for figure Fig. 1 (images a, b and c) the values used for "n_{sat}" and "c" are respectively 10 and 0.6.

Since our essential purpose in this model is the emergence of complex societies, we focused our interest on societies with a size of more than one hundred cells (which we can consider as empires). To facilitate tracking those empires, we divided the timeline (1500 time step) into periods of 100-time step each. At the end of the simulation, we got all the empires (societies with 100 cells or more) formed for each period with their necessary data. From that, we can compare between different periods and determine the variation of empires through time.

The values we chose for our parameters are: $n_{sat} = \{4; 7; 10\}$, $c = \{0.3; 0.6; 0.9\}$.

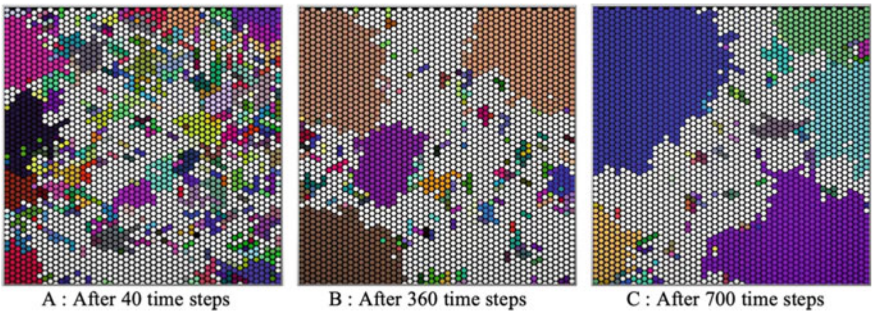

Fig. 1 **a** Image of a simulation after 40 time steps, we can only see small societies. **b** Image of a simulation after 360 time steps, we can see the rise of big societies. **c** In this image we can observe the dominance of two big empires at the time step 700

After varying values of n_{sat} and c, we got a set of simulation results where we concluded that our model kept the same logic for all the parameter combinations (we can still observe the emergence, expansion, and collapse of complex societies).The difference is in the average sizes of the constructed empires and the ability to decrease the satisfaction intensity of societies (the thing that facilitates the rise of the size).

We observe from the results that higher values of n_{sat} decrease the values of satisfaction intensity (see Fig. 4), and give empires with large sizes (see Fig. 2). However, the variable c has no direct impact on satisfaction and size variations because, after many periods, their respective values stabilize at the same value each for all the variations of c (see Figs. 3 and 5). On the other hand, the variable c affects the number of empires observed in each period so that their number decreases with the increase of the variable c (Figs. 6 and 7).

- Note: For all the graphs the number of simulations is 30, each one has 1500 unit of time. Each period equals 100 unit of time.

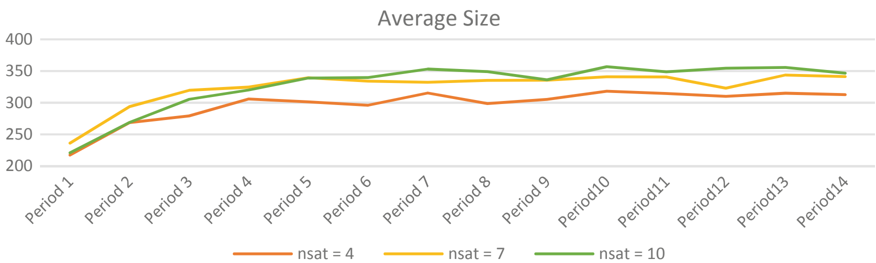

Fig. 2 Variation of the average size of empires for each period of time and for each value of the variable "n_{sat}"—for each value of $n_{sat} = \{4, 7, 10\}$ we calculate the average values of all the variations of c = 0.3, 0.6 and 0.9

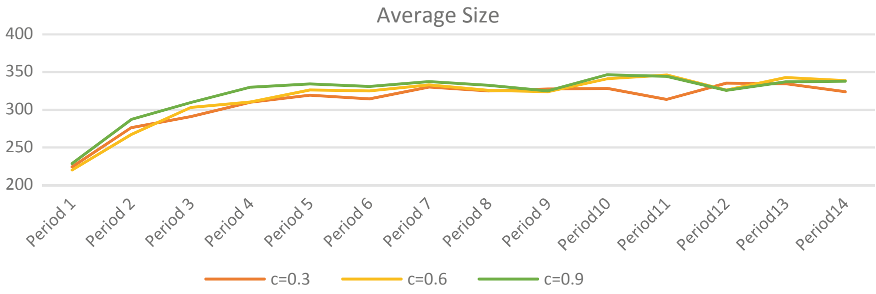

Fig. 3 Variation of the average size of empires for each period of time and for each value of the variable “c”—for each value of c = {0.3, 0.6, 0.9} we calculate the average values of all the variations of $n_{sat} = 4$, 7 and 10

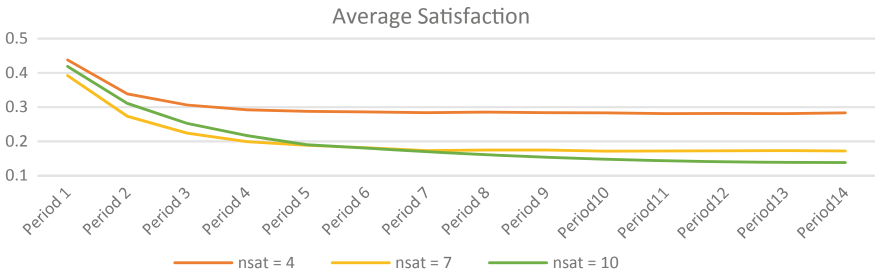

Fig. 4 Variation of the satisfaction intensity of empires for each period of time and for each value of the variable “n_{sat}”—for each value of $n_{sat} = \{4, 7, 10\}$ we calculate the average values of all the variations of c = 0.3, 0.6 and 0.9

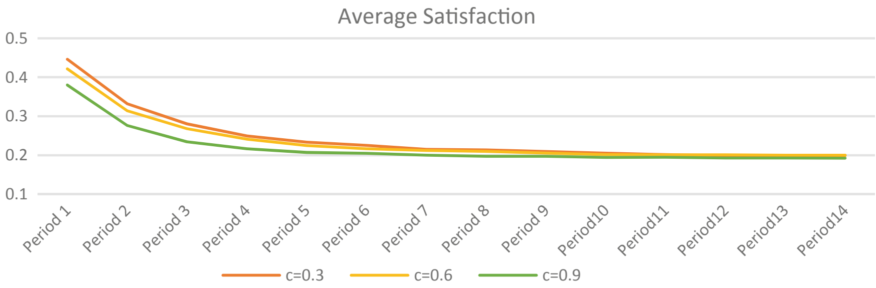

Fig. 5 Variation of the satisfaction intensity of empires for each period of time and for each value of the variable “c”—for each value of c = {0.3, 0.6, 0.9} we calculate the average values of all the variations of $n_{sat} = 4$, 7 and 10

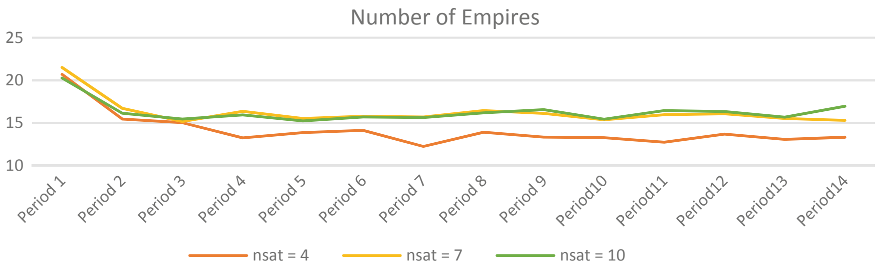

Fig. 6 Variation of the Number of Empires that emerged for each period of time and for each value of the variable "n_{sat}"—for each value of $n_{sat} = \{4, 7, 10\}$ we calculate the average values of all the variations of $c = 0.3$, 0.6 and 0.9

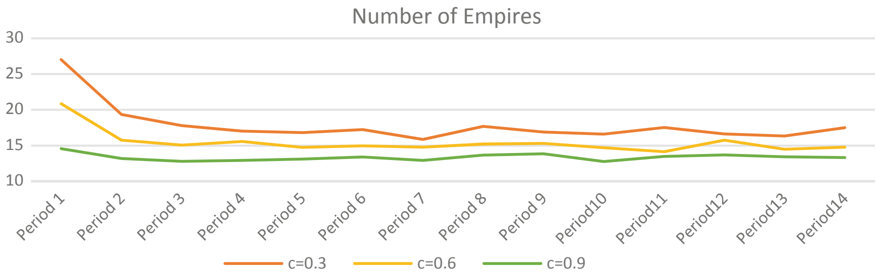

Fig. 7 Variation of the Number of Empires that emerged for each period of time and for each value of the variable "c"—for each value of $c = \{0.3, 0.6, 0.9\}$ we calculate the average values of all the variations of $n_{sat} = 4$, 7 and 10

4 Conclusion

In this paper, we present our work consisting of a simple agent-based model that explains how large-scale societies emerged in the old world. We have considered war, and repression of satisfaction as important mechanisms that control cooperation within groups. Warfare and competition between societies enhance cooperation inside groups aiming to defend their territories and common interests. Thus, the evolution of cooperation inside groups facilitates the group's expansion at the expense of other groups and hence promotes the rise of large societies.

Our work could be extended by adding geographical parameters and reimplementing the model in a realistic geographical environment. These geographical parameters will specify the type of territories: fertile lands, mountains, rivers, and seas, and will define places with intense warfare and places where the defense is easier compared to others.

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