Evolutionary Game-theoretic Modeling of Past Societies' Social Organization

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Abstract

In this work, we extend a generic *agent-based model* for simulating ancient societies, by blending *evolutionary game theory* with multiagent systems' *self-organization*. Our approach models the evolution of social behaviours in a population of strategically interacting agents corresponding to households in the *Early Minoan* era. To this end, agents participate in repeated games by means of which they exchange utility (resources) with others. The games' outcomes contribute to both the continuous re-organization of the social structure, and the progressive adoption of the most successful strategies. We present a systematic evaluation of the performance of the various strategies, assuming several variations in the way agent and organization fitness are defined, as well as in the way agents adopt new strategies. Overall, results for societies adopting this evolutionary approach, demonstrate that strategic *cooperation* is in fact an emergent behaviour in this domain. The model can provide intuitions to archaeological research, and help resolve open questions regarding the socio-economic dynamics at work in past societies.

Introduction

Agent-based modeling (ABM) began as the computational arm of *artificial life* some 20 years ago (Macal, 2009).[1] The essential features of artificial life models are translated into computational algorithms through ABM, since it is concerned with exploring and understanding the processes that lead to the emergence of order through computational means (Langton, 1995). Over the past two decades, social scientists, and in particular archaeologists, have utilized ABM for simulating ancient societies (Axtell et al., 2002; Heckbert, 2013; Janssen, 2010). At the same time, it is anticipated that incorporating ideas from artificial intelligence (AI) and multiagent systems (MAS) research in ABMs can enhance agent sophistication, and contribute on the application of strategic principles for selecting among agent behaviours (Wellman, 2016).

To this end, a recently developed ABM with autonomous, utility-based agents explores alternative hypotheses regarding the social organization of ancient societies, by employing MAS ideas and algorithms (Chliaoutakis and Chalkiadakis, 2016). The model incorporates different social organization paradigms and subsistence technologies, e.g., types of farming (Isaakidou, 2008). In particular, it employs a *self-organization* approach that allows the exploration of the historical social dynamics–i.e., the evolution of social relationships in a given society, while being grounded on archaeological evidence. However, the various social organization paradigms explored in that work assume a cooperative attitude on behalf of the agents. Specifically, agents were assumed to be willing to provide resources out of their stock in order to help agents in need, and such transfers drive the evolution of the social structure. Therefore, if one is to model societal transformation accurately, agent behaviour has to be analysed from a strategic perspective as well. In this work, we provide an alternative agent self-organization social paradigm. Agent self-organization is driven by the interactions of *strategic* agents operating within a given social organization group, and the effects these interactions have on agent utility. As such, the evolution of the social hierarchies is driven by the interaction of agent strategies in an evolutionary game-theoretic (EGT) sense (Smith, 1982; Weibull, 1997). This allows us to study the evolution and adaptation of strategic behaviours of individuals operating in the artificial ancient community, and the effect these have on the society as a whole.

In more detail, we simulate *repeated "stage games"* played by pairs of agents, corresponding to *households* in *Early Minoan* settlements located in the Malia area at the island of Crete.[2] Intuitively, the games model *resource exchanges* (utility transfers) among the households. In contrast to most matrix games studied in the literature (Perc and Szolnoki, 2010), our agents receive *non-static payoffs* (depending on their current utility, largely acquired via working the lands). Moreover, agent population is *not* constant, but fluctuates dynamically over time, due to utility-influenced births and deaths. This in effect leads to an alternative model

[1]ABM refers to both agent-based "modeling" and "model(s)".

[2]Agents correspond to *households*, which are considered to be the main social unit of production in Minoan societies for the period of interest (3,100-1,100 BCE) (Whitelaw, 2007).

to the classic fitness-based evolution strategy selection: a strategy's reproductive success depends on *dynamic* payoffs, and thus agents using the same strategy do not necessarily receive the same payoff when interacting with other agents. Each agent employs a specific strategy when playing in the stage games and after a series of (yearly) time steps agents assess and possibly modify their strategies (strategy review stage). The results of each game played contribute to the continuous alteration of the social structure, given the evolution of the differences in relative "wealth" among the agents.

Strategy review and adoption is performed in various ways. Specifically, fitness can be evaluated with respect to solely the reward achieved in the games or the overall utility of the strategic agent (derived from game-playing *and* land cultivation), thus exploring the potential differentiation on the strategic behaviours adopted by the agents in the long-term. The relative success of the agent's current strategy can be assessed at either the settlement or the societal level, with respect to the average fitness of all strategies at that level, or the average fitness of the strategy itself (calculated across agents adopting this particular strategy), while the adoption of an alternative strategy can be deterministic or stochastic.

Thus, in this paper we intertwine ABM, MAS and EGT techniques for the simulation of complex social systems. Our model uses existing archaeological evidence; and, in principle, it can readily incorporate any archaeological theory or historical data offered, in order to explore alternative hypotheses regarding the social organization of ancient societies. Though there are unfortunately no concrete existing theories for the early Bronze Age social structure (our case study here), it is interesting to note that the extensive simulation scenarios themselves provide intuitions on the social relations and strategic choices which could have linked households in Minoan society. Specifically, we present a systematic evaluation of the performance of the various strategies and their adaptation methods. Simulation results show that strategic agent populations are better sustained when: strategic agents base their strategy review decisions on the relative success of their current strategy with respect to the success of agents employing the same strategy; strategy adoption is stochastic; and the success of strategies is assessed at the settlement, rather than the entire societal level.

Background

The emerging popularity of ABM, particularly in archaeology (Dean et al., 2000; Kohler et al., 2000), is due to its ability to represent individuals and societies, and to encompass uncertainty inherent in archaeological theories or findings. Indeed, the unpredictability of interaction patterns within a simulated agent society, along with the strong possibility of emergent behaviour, can help archaeology researchers gain new insights into existing theories. Archaeologists argue that simulation studies are of considerable help in the development of explanations (Renfrew and Bahn, 2012).

A recent example for understanding how prehistoric societies adapted to the American southwest landscape of their era was presented by Janssen (2010). The respective ABM could explore to some extent how various assumptions concerning social processes affect the population aggregation and size, and the dispersion of settlements. Although agents interact with one another in that simple model, interactions are largely determined by rules that are built in the system. Another very recent example of a simulation model integrating cellular automata and a network model of the Maya social-ecological system, is *MayaSim* (Heckbert, 2013). Agents representing *Maya settlements* (rather than households), develop and expand within a landscape that changes under climate variation and anthropogenic pressure. Agents are utility-based in the sense that they estimate the utility of the various actions at hand. However, they choose actions whose utility has reached some thresholds that are in fact hard-coded by the modeler. The model was able to reproduce spatial patterns and timelines somewhat analogous to that of the Maya, although this proof-of-concept model requires refinement and further archaeological data for better calibrations.

By contrast, in the work of Chliaoutakis and Chalkiadakis (2016), the ABM incorporates a *self-organization* social paradigm, where agents within a settlement continuously re-assess their relations with others, and this affects the way resources are ultimately distributed among the community members, leading to "social mobility" in their relations. Simulation results demonstrate that when agents adopt an "egalitarian" social organization paradigm, the emerging development of many "small-size" settlements seems to be the way for survival over time. Indeed, during the Early Minoan period (ca. 3,100-2,000 BCE), reviews of archaeological evidence for the Pre-palatial society visualize a "wholy undifferentiated" landscape, comprising "very small scale autonomous local units" of a "small-scale intensive farming model", with no convincing evidence for "wealthy elites" (Haggis, 1999). When the self-organization social paradigm is adopted for determining the agents relations, a "heterarchical" social structure emerges, rather than a clear "hierarchical" structure evident in later periods.[3] Simulation results demonstrate that self-organized agent societies appear to be giving rise to larger settlements during their evolution, while both the (static) hierarchical and the self-organization paradigms maintain larger population sizes than the "egalitarian" distributive one. This fact, is in line with archaeological evidence for larger settlements (towns and "palaces") eventually coming to existence during the Middle/Late Minoan period (ca. 2,000-1,100 BCE), where a more varied and dynamic social structure is now suggested (Driessen and Langohr, 2014).

[3] A heterarchy is a system of organization where its elements are "unranked" (non-hierarchical) or possess the potential to be ranked by a number of different ways (Crumley, 1995).

Furthermore, there have been calls for the application of "evolutionary" concepts in the study of sociocultural phenomena, and the development of archaeological theories in that direction (Dunnel, 1980; Doran, 1996). The "mathematics" of evolution are the subject of *evolutionary game theory (EGT)* (Fudenberg and Levine, 1998; Weibull, 1997), which takes an interest in the *replicator dynamics* by which strategies evolve. Such dynamics typically assume that the share of the population using each strategy grows at a rate proportional to its current payoff, so that strategies providing the greatest utility against an aggregate previous period statistic grow most rapidly (Fudenberg and Levine, 1998). It is conceivable that taking evolutionary concepts into account in an archaeological theory in a principled manner, would require dealing with the "mathematics" of evolution. Moreover, EGT can be used to model exchange or trade, and thus the evolution of socio-economic behaviours relating to trade (Tomkins and Schoep, 2010). Although there are numerous related works on "standard" EGT approaches applied on MAS and ABM, such as models to determine suitable "fairness" utility functions (De Jong, 2008) or introducing behavioural diversity to study the co-evolution of a social network structure (Van Segbroeck et al., 2009), we are not aware of any archaeological ABM that explicitly adopts an evolutionary game-theoretic approach.

A utility-based ABM

We build on top of the ABM developed by Chliaoutakis and Chalkiadakis (2016) for simulating an artificial ancient society of *household* agents evolving in a grid environmental topology.[4] A household agent, containing up to a maximum number of *individuals* (household inhabitants), resides in a *cell* within the environmental grid, with the cell potentially shared by a number of agents. Adjacent cells occupied by agents make up a *settlement*—and there is at least one occupied cell in a settlement.[5] Households are *utility-based autonomous* agents who can settle (or occasionally re-settle) and cultivate to nearby environmental cells.[6] They also possess an explicit representation of the environmental grid, allowing them to choose the best available location they can migrate to, in order to improve their utility.

The total number of agents in the system changes over time, as *individuals* belonging to household-agents are born or die. While *death rate* is constant, the agent procreation ability (determining the annual levels of births of individuals within a household) is based on the amount of resources consumed by the household agent during the year.[7] This in turn depends on resources harvested, that is, the agent's *utility*, $U_x = f(population, location)$, a function inspired by the logistic map equation, the discrete version of the logistic differential equation, widely used to model population growth (Verhulst, 1838). This naive function captures the fact that labour applied on a cultivated cell increases crop yield up to a point, but at the same time a household agent cannot productively use a location forever (due to soil depletion); cultivation area is also affected by the cell's geomorphological characteristics, *i.e.* as a decay of agricultural land suitability with increasing slope, given its location on the grid.[8] Moreover, when individuals in a household exceed a critical number, new households (agent offsprings) are created; and when the agent overall utility levels are not high enough to sustain its individuals, households are "abandoned" and agents die.

Any interaction between a pair of household agents within a settlement, takes place based on their relation type: *acquaintance*, *peer* or *authority* (superior - subordinate) related agents; and these relations give rise to a social structure reflecting the flow of resources during exchanges among the agents. The authority relation depicts "superior status" of an agent x over the subordinate agent y in the context of their social organization, reflecting that higher amounts of resources flow from x to y during exchanges, than those flowing in the opposite direction; the peer relation holds between agents who are considered more-or-less equal in status (i.e. flows involve resource transfers of almost equal amounts in both directions); while acquainted agents are aware of each other's presence, but have no interaction. Agents use the information about all their past and current year resource allocations to re-evaluate and possibly alter their relations with others. These relations determine the way resources are ultimately distributed among the agents. This re-organization stage is performed within the framework of an (extended) agent self-organization algorithm (Kota et al., 2009), that results to the continuous *targeted redistribution of wealth*, *i.e.*, resources flow from the more wealthy agents to those more in need within the organization, maintaining a *dynamically* "stratified" social structure.

An evolutionary game-theoretic extension

In this work, we explore a society's evolutionary dynamics with respect to various *cooperative or not* agent behaviours. Thus, we need to introduce the ABM's main characteristics in terms of (evolutionary) game theory. Agents are con-

[4]The ABM was developed using the *NetLogo* modeling environment (Wilensky, 1999). The source code is available at http://www.intelligence.tuc.gr/ angelos.

[5]Estimated per hectare (cell) population in an agricultural settlement was set to 100 by default (Isaakidou, 2008).

[6]Note that we do not mean to argue that utility is the main factor driving human behaviour or the advance of human societies. Nevertheless, utility theory have long been adopted as useful tool in the AI domain (Russell and Norvig, 1995).

[7]These rates produce a *population growth rate* of 0.1%, when households consume adequate resources. This corresponds to estimated world-wide population growth rates during the Bronze Age (Cowgill, 1975).

[8]The input spatial information is derived from modern data and are concerning the topography, which is today's Digital Elevation Model (DEM), slope and aquifer locations (rivers and springs).

sidered as "players" in "stage games" that take place every time-step corresponding to one year. In such a game, agents exchange (harvested) resources among them via the game as follows. An agent's decisions regarding transferring resources to others correspond to its strategic "actions" in the games, and similarly, agent rewards (resource amounts transferred) are considered as "payoffs". Each game is between two agents, with agents belonging to the same settlement. At any given time-step, however, a single player may be interacting at a one-on-one basis with many other agents within the settlement simultaneously. As such, multiple stage games are taking place simultaneously within each settlement. A player remembers its interaction history with every other agent, allowing this history to be taken into account by a player's (long-term) strategy. We assume a finite, but not fixed, population size (since new households are created or old ones cease to exist).

In many domains, replication by way of simple biological reproduction is not a compelling parable for how behaviours spread in a population. In social sciences in general, replication by way of imitation and enforcement of *successful* behaviours is more appropriate (Weibull, 1997). In our work also, payoffs correspond to the decision makers' utility from interactions, and the replication mechanism is based on imitation and reinforcement of successful behaviours.

Each agent is "genetically" programmed to play originally some pure strategy k, and agent offsprings inherit the strategy the agent currently plays. An agent playing repeated stage games with opponents, sticks to some pure strategy for some time period consisting of *several* years, and then *reviews* its strategy, which sometimes results in a change of strategy. In our approach, we assume three simple player strategic behaviours: a *cooperative* one, C, willing to share resources with another player; a *defective* one, D, refusing to share resources; and one which starts with cooperation and then behaves as the other player did in the previous game round, namely *Tit-for-Tat*, TFT (Axelrod, 2006). Considering these different strategic agent types as playing games against each other, we explore the evolutionary dynamics which arise. Agents payoff is interpreted as *fitness*, depending on the relative proportions of the different strategies in the population. Success in game playing improves utility, and is translated into reproductive success; strategic agents that do well over time reproduce more, while the ones that do poorly are outcompeted. This is straightforward natural selection (Nowak, 2006). As such, household agents' effective strategies continue to be used, and ineffective ones are dropped. We now describe the games setting in more detail.

The set of pure strategies K consists of $\{C, D, TFT\}$, and an agent that uses pure strategy $k \in K$ is a k-strategist. A TFT-strategist adopts C when playing for the first time, and in every further interaction adopts C if the opponent used C; and D if the opponent used D in the previous interaction. Therefore, agent actions can be condensed to C and D. Furthermore, we assume that a stage game takes place (among household agents in a settlement) as follows: any pair of agents contract to exchange a "share" of their utility. Suppose a pair of agents x and y exchange ε_x and ε_y respectively. Assuming that each fulfills their end of the deal, thus, "cooperating", then each receives a payoff calculated as the exchange received minus the one offered, e.g. $\varepsilon_y - \varepsilon_x$ for agent x. Suppose that agent y "defects" and does not deliver as promised, then the defector will receive the respective payoff of the opponent's exchange, ε_x, while the cooperator, agent x, will lose as much as the exchange offered, $-\varepsilon_x$. If both defect, then no one gains or loses anything. If we assume agent x and y payoffs as r_x and r_y respectively, the generic normal-form representation of a game between the agents is shown below in Table 1; the arrows imply that defection is the dominant strategy for any agent (agents have incentives to "move" towards defection), and mutual defection is the only strong Nash equilibrium. Note, however, that each stage game is one with "dynamic" payoffs (since rewards depend on the current agents utility).

Table 1: Equilibria of the distribution game

		Player y	
		C	D
Player x	C	$r_y = \varepsilon_x - \varepsilon_y$, $r_x = \varepsilon_y - \varepsilon_x$	$r_y = \varepsilon_x$, $r_x = -\varepsilon_x$
	D	$r_y = -\varepsilon_y$, $r_x = \varepsilon_y$	$r_y = 0$, $r_x = 0$

Considering that there are ν players in a settlement, an agent interacts pairwise with all other $\nu - 1$ agents in the settlement. An agent is assumed to be willing to offer to opponents a portion of its total payoff. That payoff amount depends in the number of individuals, κ, that "live" in the household. Thus, the exchange ε_x offered from a household agent x, is a function of the agent's current utility U_x and κ, and has the following form:

$$\varepsilon_x = \frac{U_x}{(\nu - 1)(\kappa + 1)} \tag{1}$$

For example, a household agent with 5 individuals, is willing to contribute to its $\nu - 1$ "opponents", $U_x/6$ of its utility, offering to each of its opponents $(U_x/6)/(\nu - 1)$ reward during a game interaction. Note that Eq.1 depends on agent utility U_x, which depends on resources harvested (and not just on resources received through games). At the end of each year, agents update their utility and reorganize their relations, based on their accumulated rewards via the games. The *total payoff* $r_t(x)$ from games for a k-strategist x at time t is:

$$r_t(x) = \sum_{\forall y \in O} r_x(i, j) \tag{2}$$

where O is the set of x's opponents at t (and i, j are the actions prescribed by x's and y's strategies during an interaction). The *updated* utility $\tilde{U}_x$, of an agent x is calculated as:

$$\tilde{U}_x = U_x + r_t(x) \tag{3}$$

Note that for a D-strategic agent x, it is $\tilde{U}_x \geq U_x$ always, as such a player is unwilling to make any exchange, but may receive some reward from a cooperative contracted agent.

Now, the classic evolutionary model of *replicator dynamics*, assumes that a homogeneous population playing a particular strategy grows in proportion to how well that strategy is doing relative to the mean strategy population performance (Fudenberg and Levine, 1998). Since the agent population in our ABM is not constant, but fluctuates depending on agent utility, and since agents do not "identify" with strategies (but may adopt other strategies over time), we formulate the evolutionary dynamics based on evaluating *agents*', rather than strategies' fitness. Therefore, at any given time step t, the current *fitness* $f_t(x)$ of an agent x , is calculated as:

$$f_t(x) = \tilde{U}_x \tag{4}$$

Although we believe it is more natural for an agent to evaluate its fitness based on its utility, since population growth is utility-dependent in our ABM, in order to be in line with classic EGT approaches, in some simulation scenarios we also considered agent fitness to be based solely on its total reward from games it participated in. In those scenarios, agent x calculates its fitness at time t as:

$$f_t(x) = r_t(x) \tag{5}$$

At the end of some time period T, during which the agent plays games using strategy k, agent x evaluates its current fitness *wrt.* to the average fitness of the organization, before (possibly) switching to any other strategy. The *average fitness* F of the organization over the period T, is calculated as:

$$F = \frac{1}{n} \sum_{\forall x \in S, \forall t \in T} \frac{f_t(x)}{|T|} \tag{6}$$

where $S = \{x_1, x_2, ...x_n\}$ is the set of all household agents in the organization, considering each agent's lifetime during period T. The term "organization" may actually refer to either the settlement in which x belongs, or the entire society of agents (across all settlements). Although agents always play games only with other agents in their settlement, in some simulation scenarios the set S in Eq. 6 above refers to the entire society. This attempts to capture the fact that the views of the entire society regarding the value of the various behaviours (strategies), could weigh on an agent 's deliberations regarding the adoption of a specific "attitude" towards others. Moreover, assuming that agent x reviewing its strategy is currently a k-strategist, in some simulation scenarios we also calculate F *wrt.* to the set S_k of k-strategists in the organization (settlement or society) . That is, in Eq. 6, we replace S (the set of agents in the organization) with S_k (the set of agents in the organization that share x's strategy). This attempts to evaluate how well x is doing *wrt.* agents exhibiting the same "attitude" towards others.

Agent x will consider switching to some other strategy, only if $f_t(x) - F < 0$, i.e., its fitness is less than the average fitness of the organization under examination (settlement or entire society) during the previous period T. If that condition holds, x can choose to *deterministically* switch to some other pure strategy l: it simply switches to l with $max\{F_l\},\ l \in K$, where F_l is the average fitness of the l-strategic agents in the organization; or it can *stochastically* switch to some l with probability p_{kl} $(k, l \in K)$, based on the percentage of l-strategic agents (or l-strategists) in the organization, calculated as follows:

$$p_{kl}(x) = \frac{|S_l|}{n} \tag{7}$$

Note that, in that case, p_{kk} is considered to be the probability that a reviewing k-strategist does not change strategy.

Regardless of the strategy review scenario used, self-organization is now driven by the interactions of *strategic* agents operating within a given social organization group. However, the re-organization (decentralized structural adaptation) stage, used for re-evaluating and potentially altering agent relations, is the same as in the original ABM (Chliaoutakis and Chalkiadakis, 2016).

Simulations and results

We evaluate the impact of the evolutionary self-organization social paradigm to population viability and strategic behaviours that may emerge in the long-term. We note that model parameters were initialized to values set so that they correspond to archaeological records or estimates found in archaeological studies relevant to the period of concern, such as estimated per hectare population in an agricultural settlement, resources amount required per individual per year, agriculture production per year, etc. (Isaakidou, 2008; Bevan, 2010). The number of initial settlements per scenario was set to 2, and the number of household agents in a given settlement was initialized to a random number between 1 and 10. Moreover, a cell's initial resources amount at a given run is multiplied with a sample from a standard normal distribution, and thus varies across runs. We consider also a uniform distribution of initial strategies, depending on agents numbers within a settlement for every simulation run. In our simulations, agents *(i)* never review their strategy; *(ii)* review their strategy and perhaps deterministically switch to another; or *(iii)* review their strategy and perhaps stochastically switch to another. Furthermore, we consider review *time periods* of either 8 or 16 years ($T = 8$ or $T = 16$). In total, 33 experimental scenarios were simulated, and each scenario was simulated for thirty (30) runs, for a total of 990 simulation runs = 30 (runs for the "no review" scenario) +

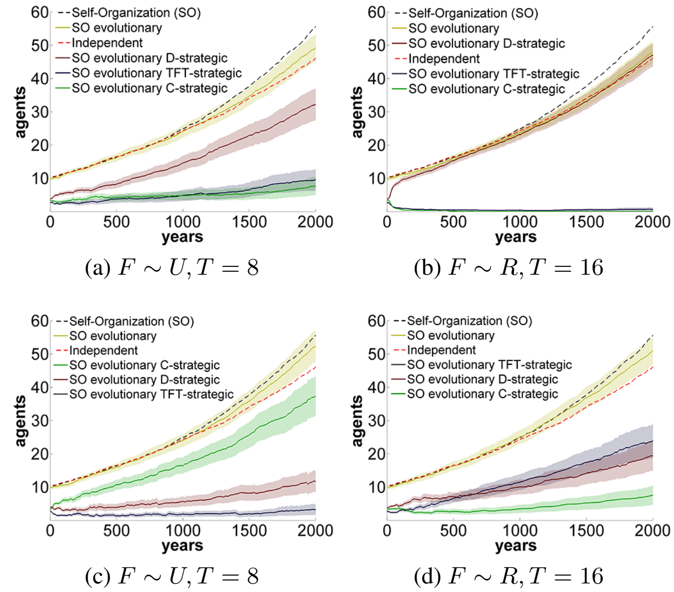
30×2 (strategy review options) $\times$ 2 (fitness function evaluated *wrt.* U or r_t) $\times$ 2 ($T = 8$ or $T = 16$) $\times$ 2 (organization is settlement or entire society) $\times$ 2 (all agents in the organization or only *"same-as-the-agent"*-strategists are considered). Moreover, the random number generators introduced in parts of the model are obviously "pseudo-random". Thus, via using the same random "seeds", one may introduce the same opportunities for agents in the model simulations (i.e., same "random" initial agent locations etc). In this way, our simulations are reproducible. Now, we compare the performance (in terms of population growth achieved) of strategic agents that play games and use self-organization, which we term "SO evolutionary" agents, against those that *(i)* self-organize (SO) but do not play games and always help those in need if their utility permits it, or *(ii)* adopt an "independent" social behaviour, trying to maximize their utility without interacting with others. We also report on the fraction of the population that adopts a cooperative attitude at each scenario (*cf.* Table 2). The percentage of cooperative or defective behaviour includes the current C or D actions of the TFT-strategists.

In our first scenario, there is no strategy review for the "SO evolutionary" agents. We report that agent population size increases with time, at a rate that ranges between those of the extremes (benevolent "SO" agents that always help each other, and "independent") in the model, while their social behaviour remains proportionally stable, i.e. $\approx 50\%$ of the agents cooperate or defect; we report that TFT-strategists actually exhibit $\approx 60\%$ of *cooperative* behaviour. Let us now discuss our findings for the rest of the scenarios.

We adopt the notation: $F \sim U$, where agents fitness function is calculated by their updated utility (Eq. 4) and $F \sim R$, where agents fitness function is calculated by their total accumulated reward (Eq. 5). Moreover, figure legends are ranked in accordance to the relative performance of their corresponding behavioural methods.

We now simulate agents which review their strategy k and *deterministically* switch to strategy l with $max\{F_l\},\ l \in K$, where F_l is the average fitness of the l-strategic agents in the organization. Results for all scenarios in this category, regardless of the organization being the settlement or the entire society (not shown here), have similar behaviour to the ones shown in Figure 1a, when $F \sim U$, and Figure 1b, when $F \sim R$. We observe an overall decline of the average population of "SO evolutionary" agents, irrespective of agent's strategy review time period and fitness function. Moreover, results for scenarios where $F \sim R$ (Figure 1b) are as anticipated by the game equilibrium (Table 1), that is, a totally defective behaviour. When $F \sim U$ (Figure 1a), however, we observe that cooperative behaviour is not completely extinct. Regardless, agents adopt, on average, a defective behaviour: $\approx 50 - 75\%$ of the agents defect when $F \sim U$, and $\approx 95 - 100\%$ when $F \sim R$ (*cf.* Table 2).

We also simulated scenarios where agents review their strategy k and *stochastically* switch to strategy l with probability $p_{kl},\ k, l \in K$, based on the percentage of l-strategic agents in the organization (*cf.* Eq. 7). Likewise, results for all scenarios in this category have similar behaviour to the ones shown in Figure 1c, when $F \sim U$, and Figure 1d, when $F \sim R$. There is now a noticeable increase on the average agents population, as well as in the average numbers of agents adopting a *cooperative* strategy (while the average numbers of D-strategists decrease contrariwise).



(a) $F \sim U, T = 8$

(b) $F \sim R, T = 16$

(c) $F \sim U, T = 8$

(d) $F \sim R, T = 16$

Figure 1: Agent population over 2,000 (yearly) time-steps for scenarios with (a, b) *deterministic* and (c, d) *stochastic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*. Error (shading) bars indicate 95% confidence intervals.

We can report that cooperative behaviour is emergent in 24 out of the 33 scenarios, with highest average numbers observed when agent interactions are local and updating is stochastic, as shown in Table 2. Moreover, cooperative behaviour is more prevalent when $F \sim U$ rather than $F \sim R$. This is quite natural: one expects agents that evaluate fitness taking into account their *reward* in games only, to tend to become more aggressive or opportunistic; while taking into account their overall *utility* tends to smoothen such behaviours. Since the non-strategic, cooperation-oriented "self-organizing" agents, and the non-interacting, "independent" agents, can be viewed as constituting two near-extremes in terms of strategic behaviour, it is expected that the average aggregate population of the strategic agents will lie largely between their corresponding ones. Indeed, simulation results confirm this intuition. Overall, scenarios that sustain a higher average population of "SO evolutionary" agents, are apparently those where agent fitness is evaluated *wrt. utility*. This choice of conditioning strategy evo-

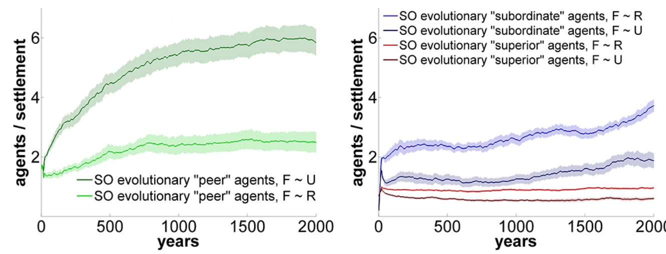
Table 2: Average cooperative behaviour (including the cooperative behaviour of the TFT agents) rates for all scenarios, where every k-strategist considers either the set S_k of k-strategists or the set S of *all* agents within the organization (*settlement-group* or *society*), reviewing its strategy either *deterministically* or *stochastically*.

Cooperation rates (%)	Deterministic				Stochastic			
	Group		Society		Group		Society	
	S	S_k	S	S_k	S	S_k	S	S_k
$F \sim U$, $T = 8$	38	37	35	37	34	**70**	24	34
$F \sim R$, $T = 8$	0	0	7	0	0	**37**	10	23
$F \sim U$, $T = 16$	44	25	37	27	49	**56**	42	46
$F \sim R$, $T = 16$	0	2	0	0	0	**60**	7	14

lution on overall utility rather than reward is justified from the results, while it does make sense from a socio-economic perspective: you choose how much to "exchange" based on your overall well-being. Specifically, better performance is observed when agent fitness is compared to that of the *settlement* group, rather than the entire society; and especially when the agents' performance is evaluated *wrt.* the average fitness of the strategy itself, calculated across agents adopting this particular strategy; and the adoption of an alternative strategy is stochastic. Notably, the scenario with high percentages of emergent cooperative behaviour also appears better in sustaining higher agents population (*cf.* Figure. 1c).

We also report that the resulting social structure is indeed correlated with the agents' strategic behaviour. In Fig. 2, we observe that the numbers of *peer* related agents are higher on average when $F \sim U$, while the numbers of *superior* and *subordinate* agents are higher on average when $F \sim R$. This is quite expected, since when $F \sim U$ agents are more cooperative, rendering the differences in utility among them less acute—and thus the *authority* relations are fewer in that case. Interestingly, the higher number of peer agents corresponds to scenarios with higher *cooperative* behaviour percentages observed in all simulations.

We have also applied a basic *sensitivity analysis* process to determine how sensitive our ABM is to the particular set of initial conditions that we used. In particular, we have run simulations involving an initial average population of 100 agents, with similar results, although with lower levels of corresponding cooperative behaviour that seem to be decreased with time. Thus, we do not anticipate that a higher initial population of agents will substantially change



(a) Peer relation (b) Authority relation

Figure 2: Average number of **(a)** peer and **(b)** authority related agents per settlement for all scenarios, over 2,000 years.

the conclusions drawn from our work here. Moreover, we conducted additional experiments, with different initial distribution of strategies each, giving higher rates to each of the assumed strategic behaviours. The setting that was favouring TFT, demonstrated both the highest cooperation levels and also the highest population sizes observed in all our experiments. Due to space restrictions we do not report on those results further.

Conclusions

Building on key EGT concepts, we simulated a series of repeated games with *non-static* payoffs, played among a finite but not *constant* population of autonomous strategic agents, representing Early Minoan "households". In particular, we simulated the households' behavioural evolution when interacting by *exchanging resources* among themselves by assuming that exchanges are modeled via two-player games, and considering various scenarios and initialization setups. The strategic agent interactions, and their effects on agent utility, drive the continuous re-organization of the social structure, and naturally lead to the survival of the most successful strategies. The focus on agent, rather than strategy, fitness, is a departure from "standard" EGT, and allows us to deal with problems like the one here.

Model results indicate that scenarios that are better in sustaining higher agents population are those at which agents adopt new strategies in a stochastic manner and agent performance is compared to that of their immediate community—especially to that of agents in the group that adopt the same strategic behaviour—rather than the entire society. In these scenarios, agent populations converge to adopting cooperative strategies, despite this behaviour being in contrast to that prescribed by the stage game Nash equilibrium. Furthermore, results are in line with the view that, though complex societies emerge to a large extent due to conflict and competition, these social conditions seldom exist without cooperative agreements, alliances and cooperation networks in societies (Service, 1975; Gumerman, 1986).

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