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ASYNCHRONOUS ACTIVATION IN SPATIAL EVOLUTIONARY GAMES

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Abstract. Situations where honest people interact with dishonest people are ubiquitous. Problems emerge spontaneously and leaders must face the situations accordingly. In any civilized society honest people respect the laws while dishonest people do not. Decision makers need to take proper measures in order to avoid emergence of social problems as a consequence of dishonest behavior.

Studies proved that in order to discourage social dishonest behavior, punishment probability is more important than punishment severity. Honest/dishonest dynamics are analyzed within the Social Honesty game. Transition intervals for punishment probability are indentified and analyzed.

The following paper illustrates how the punishment probability influences the outcome of interactions between players, using asynchronous models of activation.

1. Introduction

Dishonest actions often cause social problems and decisions are needed in order to maintain stability and satisfaction amongst the people. Real-world situations reveal that there are no utopian societies. Individuals choose dishonest behavior for their own personal gain when the punishment probability is low or the punishment severity can be compensated by the benefits as a result of their decisions [6]. Interactions between individuals are actually transactions [13], moreover a dishonest strategy used by a dishonest player leads to a greater payoff for the latter [13]. That kind of benefit can be seen as a payoff of crime [11].

Different models of analysis of social interactions are used. A new game called Social Honesty is proposed. Interactions between individuals are based

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on imitation. Amongst any other species humans have proved to be the most adaptable of species. We have the most well developed sense of cooperation [4, 16]. For the dishonest players to succeed honest players must be present in the game.

Honest/dishonest interactions are analyzed within the fields of Cellular Automata and Evolutionary Game Theory (GT). Punishment has a crucial role in deterring dishonest behavior. Social experience has shown that a low probability of punishment is ineffective in promoting honest behavior, even if the severity is high [1]. A classical example is the United States Prohibition.

In real complex systems synchronous activation is rarely seen. Nature finds different landmarks for individuals to operate, whether we talk about people, animals, plants or any other beings. Biological systems tend to reorganize or to find landmarks according to an internal biological clock or natural phenomena that affect the environment or human intervention. The studies made in the Social Honesty game [13] proposed a synchronous activation of players. Since in real situations players choose if they want to play or not, we propose different models of asynchronous activation, based on Cellular Automata, like Random Order Schema and the Clock Schema [7].

In this paper we study the effects of asynchronism over the "p-transition intervals" and critical values for punishment probability. Honest and dishonest players tend to organize themselves into clusters from the first rounds of interaction. We call a transition interval an interval of punishment probabilities where the percentage rate of honest players changes from 0% to 100%. The probabilistic payoff determines what kind of strategy a player is choosing for the next interaction [13].

The following paper is organized as follows: Section 2 presents the asynchronous activation in Social Honesty game together with experimental results using different models of asynchronous activation, the presence of asynchronism in biological systems is presented in Section 3 and conclusions and directions for further research in Section 4.

1.1. **Activation mechanisms.** In order to implement asynchronous mechanisms of activation, we use the following models:

The Random Order schema defines randomly the players who will activate for every round [7]. The study tested a p_r=*0.5* probability for any player to interact with other players (p_r-probability of acting with the Random Order schema). If a player is not active then no interactions with other players are possible.

The Clock schema defines a period of activation for each player by assigning a timer [7]. The period of activation is set at random for each player for a maximum of 5 rounds. Every round is considered to be an increase of the timer for every player. If the timers have exceeded the period defined, the states are updated and the timer is set to zero [7].

The Cyclic schema defines at each time step a node to be chosen according to a fixed update order, which was decided at random during initialization of the model [19].

Finally we use a combination of the two methods. Players activate synchronously with a subgroup of players activating according to the Clock schema. The probability for a player to activate according to the Clock Schema was set to $p_c = 0.5$. A subgroup of maximum $N/2$ players (where $N \times N$=total number of players) where randomly defined in order to activate according to the Random Order schema. Any player activating according to the Clock schema can also activate according to the Random Order schema with a probability of p_r=0.5.

2. Asynchronous activation in Social Honesty model

The moral standards of a society, traditions, customs etc. influence the way individuals take decisions. Assuming traditions, morality, customs, laws, education to be more than necessary for a individuals personal success would be improper. The Social Honesty (SH) game analyses human interaction based on imitation.

For convenience we call an H-player a player who chooses a honest strategy and a D-player is a player who chooses a dishonest strategy [13].

The matrix of the Social Honesty game [13]:

Player 1/Player 2	*Honest (H)*	*Dishonest (D)*
Honest (H)	*c, c*	*0, A*
Dishonest (D)	*A, 0*	*B, B'*

Players in the SH game get certain payoffs as follows: - if two H-players interact, the payoff for each player is $c>0$; - if an H-player interacts with a D-player, the H-player gets a payoff equal to 0 and the D-player is punished with the probability p_1. If not punished the D-player gets the payoff a ($a>c$) [13].

The D-players payoff can be described as a random variable A [13]:

$$A = \begin{pmatrix} -S & a \\ p_1 & 1 - p_1 \end{pmatrix}$$

Interactions between two D-players lead to the following:

- each one of them may be punished with probability p_2;
- if none of them is punished then only one gets a positive payoff b [13] and the other gets 0.

The payoffs for each D-player, can be described as the next variables B and B' [13]:

$$B = \begin{pmatrix} -S & 0 & b \\ p_2 & \dfrac{1-p_2}{2} & \dfrac{1-p_2}{2} \end{pmatrix}$$

and

$$B^{'} = \begin{pmatrix} -S & 0 & b \\ p_2 & \dfrac{1-p_2}{2} & \dfrac{1-p_2}{2} \end{pmatrix}$$

Experiments were made with two values of N: *100* and *200*, using Moore neighborhood [14], and the '*survival of the fittest*' principle [18] as the update strategy, each player imitates the one with the highest payoff. If a player is not active during a round then he cannot imitate another player and cannot be imitated. We use the same punishment severity *S=2*.

2.1. **The Transition Interval for Asynchronous Updating Mechanisms.** We study the effects of asynchronous activation on an initial population of 100×100 and 200×200 players, with 50% Honest players and 50% Dishonest players distributed randomly. We set *S=2* and use different punishment probabilities (p). Transition intervals reveal the changes in *H/D* players rate. It can be observed that the fluctuations are much greater using the Clock schema combined with the Random Order schema as shown in Fig. 3, than using only the Clock schema as a asynchronous mechanism of activation (see Fig. 1).

When using the Random Order schema, the transition interval is much smaller than when using the combination of the two schemas. (Fig. 2). The effect of randomness leads to a faster change in *H/D* players rate in the case of Random order. However activation using the Clock schema leads to more stable results in time (see Fig. 4) than the Random order schema (see Fig. 7).

Tests show that when players act according to a certain rule, rather than randomly, the population of H-players is much more stable in time, even if the fluctuations are present.

In Fig. 1 the transition interval for players activating according to the Clock schema, is significantly larger than in Fig. 2, for players using the Random order schema. For smaller changes of p, the players rate changes. H-players are able to dominate for values of p greater than the maximum value of the transition interval. Increasing the maximum number of cycles will increase the value of the two limits of the transition interval. The size of the transition interval remains the same.

The transition intervals for$p$ are shown in the next table:

Activation mechanisms	100×100 players	200×200 players
Synchronous	0.12 - 0.18	0.12 - 0.18
Clock	0.22 - 0.26	0.22 - 0.26
Random Order	0.28 - 0.29	0.28 - 0.29
Cyclic	0.233 - 0.238	0.233 - 0.238
Clock schema and a subgroup of players activating randomly	0.22 - 0.26	0.22 - 0.26

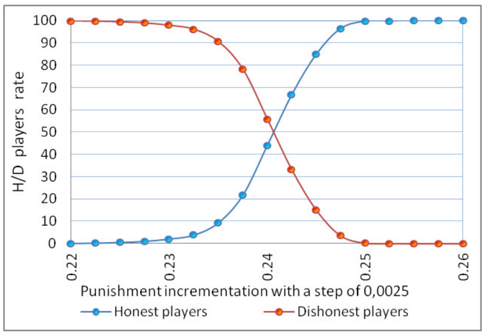

Fig.1a. Asynchronous activation using the Clock schema (N=100)

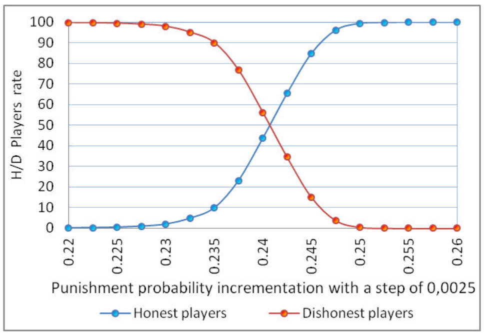

Fig.1b. Asynchronous activation using the Clock schema (N=200)

Simulations of the game using the clock schema start with 50% honest players distributed randomly. Fig.1a and 1b show the transition intervals for the clock schema. Results were obtained over an average of 100 repetitions, each repetition with 20000 rounds and a punishment severity of S=2. When increasing the value of p we notice that the honest players rate changes with few fluctuations. The clock has a maximum of 5 cycles, chosen independently and randomly for each player. The transition interval reveals fluctuations in the player percent rate (see Fig.4a, 4b and 6). The percentage of honest players increases along with the incrementation of p while the number of dishonest players decreases down to 0%, leading to a honest domination with values of p greater than the upper limit of the interval.

Simulations of the game using the Random Order schema start with 50% honest players distributed randomly. Fig.2a and 2b reveal the transition intervals for the Random Order schema. Results were obtained over an average of 100 repetitions, each repetition with 20000 rounds and a punishment severity $S=2$.

Each player has a probability of p_r=0.5 to play. Experiments reveal that the transition interval is smaller than the transition interval for the clock

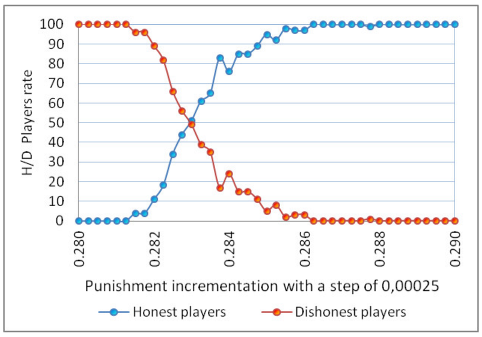

Fig.2a. Asynchronous activation using the Random Order schema (N=100)

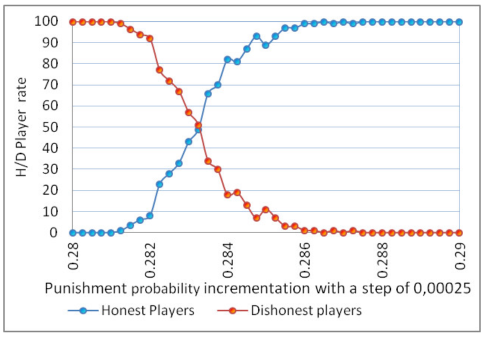

Fig.2b. Asynchronous activation using the Random Order schema (N=200)

schema, with greater fluctuations. The random effect causes dramatic changes in the game outcome. For values of p lower than 0.29 in the transition interval, there is no constant increase in the percentage rate of honest players.

The transition interval for asynchronous activation with the Random Order schema does not change for greater populations, however increasing p_r will lower the values of the limits of the transition interval.

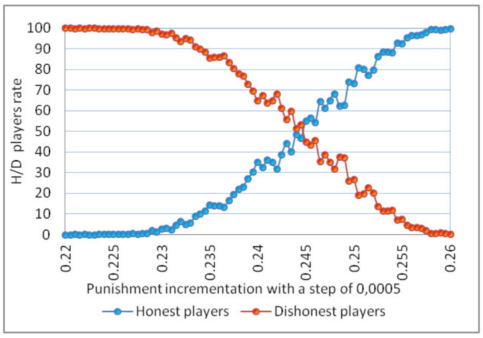

Fig.3a. Asynchronous activation using the Clock schema and a subgroup of players activating randomly (N=100)

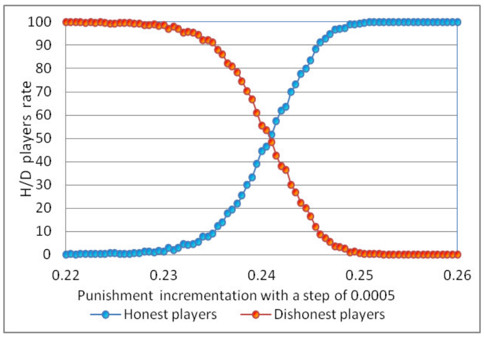

Fig.3b. Asynchronous activation using the Clock schema and a subgroup of players activating randomly (N=200).

Fig. 3a and 3b reveal the transition intervals for the simulations using the combination of schemas. The game starts with 50% honest players distributed randomly. Results were obtained over an average of 100 repetitions, each repetition with 20000 rounds, with a punishment severity of S=2. Starting from a synchronous model of activation we define a subgroup of players activating according to the Clock schema. Every player has a $p_c = 0.5$ chance to activate according to the Clock schema. Another subgroup of players chosen randomly, no more than *N/2* of total players, are activated randomly with a probability of p_r=0.5.

The random effect causes greater fluctuations than using the Clock schema (see Fig. 1).

Increasing the number of player will result in greater values for the margins of the transition interval, the borders having higher values. This might be a good explanation for the need of a greater punishment probability in larger populations that are much harder to control. For smaller changes of p, the number of H-players changes significantly. Increasing p to the upper level of the transition will eventually lead to a H-player domination.

Transition intervals may very well explain how people react and accept new social values in transition states, or sudden changes of a political regime. Lack of democratic laws and inefficient institutions in Romania and other former communist countries after December 1989, caused social problems like: increased crime rate, public riots (miners riots), high unemployment rate and also government instability.

Sudden changes often cause uncertainty and lack of predictability, that leads to dishonest behavior and erosion of social capital [10]. Dishonest behavior becomes a convenient choice when punishment probability is low, or opportunities for faster and easier payoffs appear due to the lack of regulations.

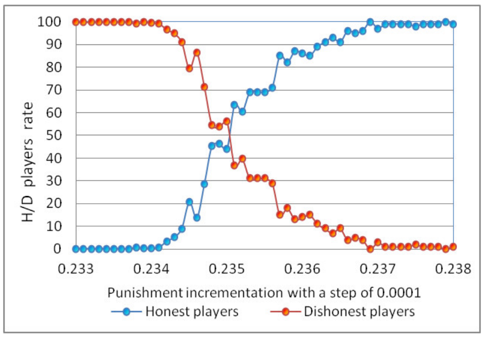

Fig.4a. Asynchronous activation using the Cyclic schema (N=100)

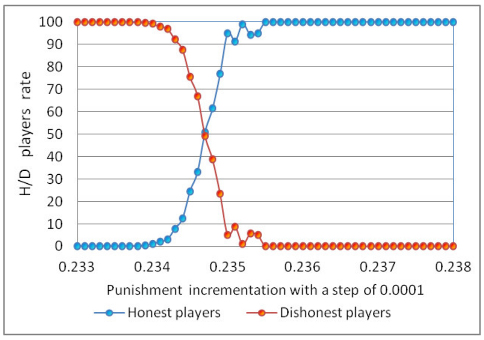

Fig.4b. Asynchronous activation using the Cyclic schema (N=200)

Simulations of the game using the Cyclic schema start with 50% honest players distributed randomly. Results were obtained over an average of 100 repetitions, each repetition with 20000 rounds, with a punishment severity of S=2. When increasing the value of p we notice that the honest players rate changes with fluctuations depending of the size of the world. The cycle used in the simulations is 3. The transition interval reveals fluctuations in the player percent rate. The percentage of honest players increases along with the incrementation of p while the number of dishonest players decreases down to 0%, leading to a honest domination with values of p greater than the upper limit of the interval.

The transition interval does not change for larger population, but the fluctuations are smaller. Using the cyclic method we find a much smaller transition interval.

2.2. **World dynamics using the Clock schema.** We use two values for N, namely 100 and 200, and start with 50% Honest players and 50% Dishonest players, distributed randomly. We set S=2 and use different punishment probabilities. Experiments reveal fluctuations from up to 30% in the percent of honest players (see Fig. 5a, 5b and 7). Honest and dishonest players coexist even after 200000 rounds.

Incrementation of p from the lowest values of the transition interval to its highest values leads to a constant increase in H-players percent rate. A dynamic equilibrium can be established between H-players and D-players. Clusters of H-players emerge from the beginning of the game and are stable up to 200.000 rounds. During the game the clusters grow and change their shape. The frontiers of the clusters are not stable and honest players are replaced with dishonest players. D-players organize into clusters similar to H-players clusters.

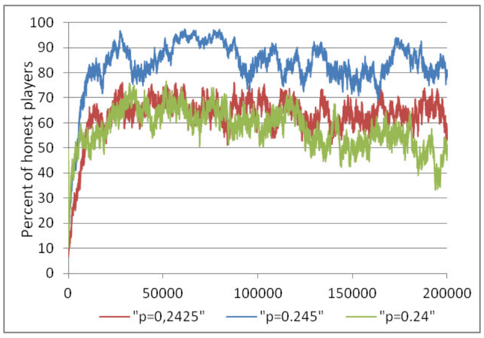

Fig.5a. Asynchronous activation using the Clock schema (N=100)

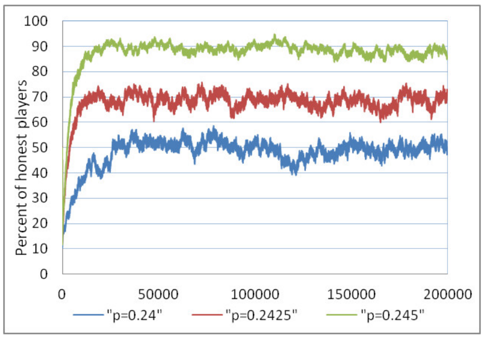

Fig.5b. Asynchronous activation using the Clock schema (N=200)

Fig.5a and 5b reveal the dynamics of the world using the Clock schema with two different values of N and three different values of p for each value of N. Clusters of honest players and dishonest players coexist even after 200000 rounds. The honest players need to organize into greater clusters in order to survive (see Fig.7). Increasing the number of players results in smaller fluctuations. By taking a first look at Fig.5a and 5b we notice that the larger the population becomes the smaller the fluctuations are. Larger populations prove to be more stable in the percentage of honest players. The moral values and a honest contagion increases for greater populations. Fig.6 and 7 are representations of synchronous and asynchronous models of player activation. Synchronous activation allows H-players to maintain a stable rate after 300 rounds, while asynchronous activation allows a stable rate of H-players after 50.000 rounds. When players act asynchronously the clusters need a longer time to form and maintain stability. The size of the clusters is significantly larger and it can be noticed that changes take place at the margins of the clusters.

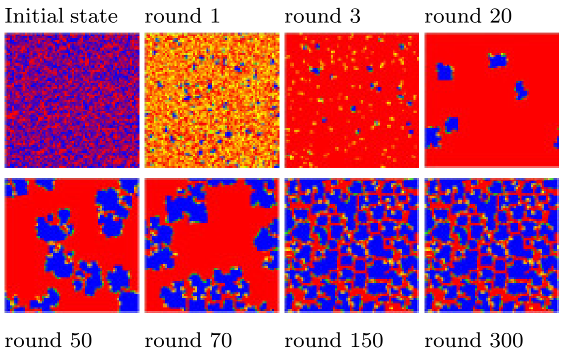

Fig.6. Synchronous activation of players

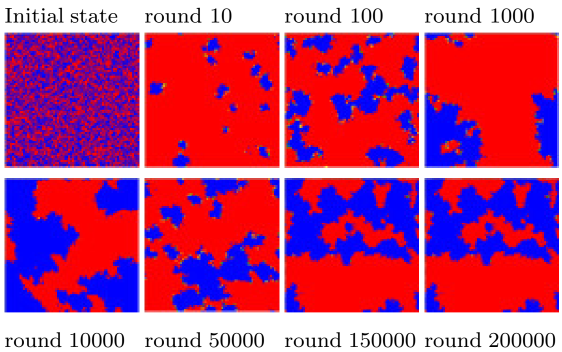

Fig.7. Asynchronous activation using the Clock schema

Fig.6 depicts the honest players cluster formation using S=2 and p=0.15 and the synchronous schema of activation. The initial population contains 50% honest players. In the first rounds H-players percentage drops to around

2%. Clusters of H-players become larger up to 57% and remains stable after 300 rounds. The color representation is: blue - is honest/was honest; red is dishonest/was dishonest; green - is honest/was dishonest; yellow - is dishonest/was honest.

Fig.7 reveals the emergence of clusters of honest players from the beginning of the game. Initial population contains 50% honest players distributed randomly. We set S=2 and p=0.24. Clusters of honest players are still present even after 200000 rounds and beyond. The size and shape of the clusters are different than those present in synchronous activation. The margins of the cluster are the most affected by changes of strategy. The position of the clusters changes due to the effect of increasing p. A dynamic equilibrium can be established after 50000 rounds and maintained for indefinite periods of time.

2.3. **World dynamics using the Random Order Schema.** A random mechanism of activation makes impossible for honest players to coexist with dishonest players for longer periods of time. Fig.8 shows that for small changes in the punishment probability the honest players percent rate changes from 0% up to 100%. The transition interval is smaller than using the Clock schema.

When players act randomly there is no dynamic equilibrium between H-players and D-players. Clusters of H-players are unable to maintain stability for values of p lower than 0.284. Increasing the value of p_r will eventually lower the values of p, where H-players are able to dominate.

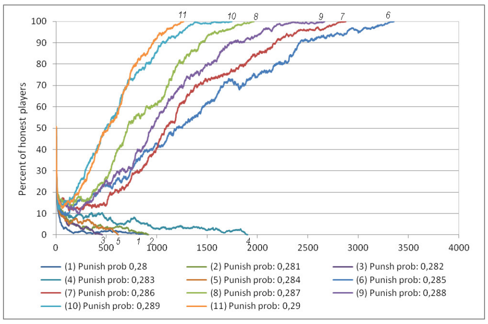

Fig.8a. Asynchronous activation using the Random Order schema (N=100)

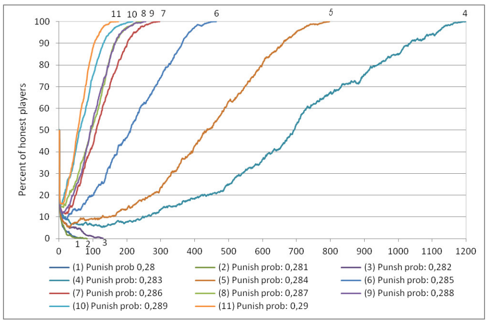

Fig.8b. Asynchronous activation using the Random Order schema (N=200)

Fig. 8a and 8b reveal that in the transition interval there is no balance between honest players and dishonest players. Different values for p lead either to D-player domination or H-player domination. A lower punishment probability will result in a complete honest players extinction. For values of p greater than 0.29, honest players are able to replace all dishonest players.

A random activation of players cannot establish a dynamic equilibrium over long periods of time. The outcome of the game remains the same for different runs of the same value of p. This situation is not influenced by the number of players. Players activating randomly, fall in one of the two extremes: either they are all honest or they are all dishonest. This situation leads to the assumption that players make extreme choices when rules are no longer applied.

When people lack proper guidance or management and act randomly societies find difficult to achieve stability. Regulations and proper management lead to stability and honest contagion. The effects on random activation can be easily observed in transition states where insufficient laws make authorities passive to dishonest behavior. Individuals find the law of the jungle more appropriate to satisfy their social and basic needs.

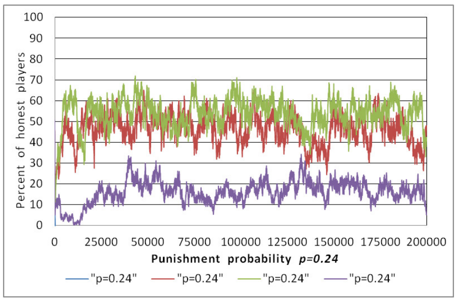

Fig.9a.Activation using the Clock schema and a subgroup of players activating randomly (N=100,p=0.24). Each color represents a distinct run with the same punishment probability p=0.24

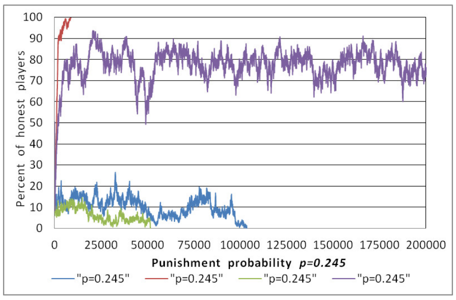

Fig.9b.Activation using the Clock schema and a subgroup of players activating randomly (N=100,p=0.245). Each color represents a distinct run with the same punishment probability p=0.245

2.4. **World dynamics using the Clock Schema and a Subgroup of Players Activating Randomly.** Fig. 9a, 9b, 9c, 9d, 9e, 9f reveal the dynamics of the world for two different values of N, and three different values of p for each value of N. We run experiments for 200.000 rounds and four different runs for each value of p. Each colored graph represents a different run of the game with the same value of p.

Clusters of honest players emerge from the beginning of the game, but this combination of methods does not ensure stability in time for various runs of the same values of p, due to the random activation of players. However at first look we notice that for larger populations the fluctuations in the honest player percent rate become smaller.

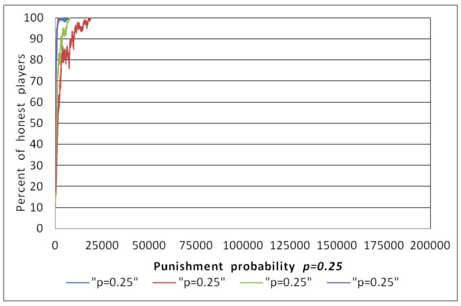

Fig.9c.Activation using the Clock schema and a subgroup of players activating randomly (N=100,p=0.25). Each color represents a distinct run with the same punishment probability p=0.25

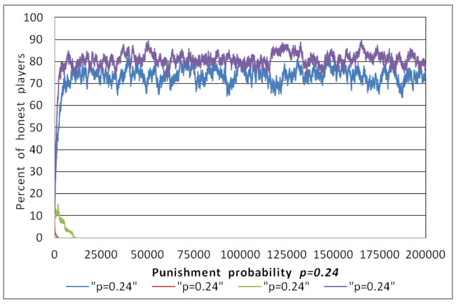

Fig.9d.Activation using the Clock schema and a subgroup of players activating randomly (N=200, p=0.24). Each color represents a distinct run with the same punishment probability p=0.24

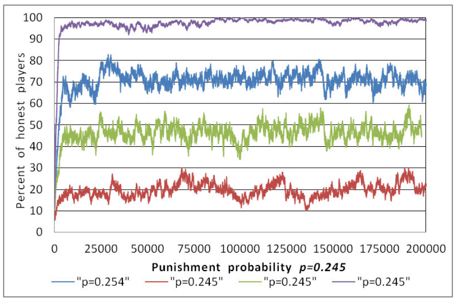

Fig.9e.Activation using the Clock schema and a subgroup of players activating randomly (N=200, p=0.245). Each color represents a distinct run with the same punishment probability p=0.245

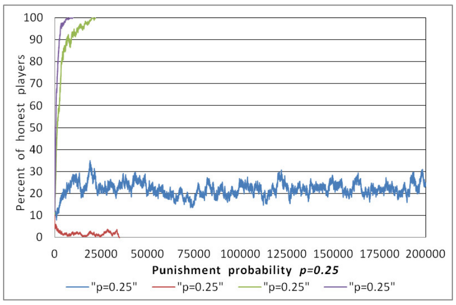

Fig.9f.Activation using the Clock schema and a subgroup of players activating randomly (N=200, p=0.25). Each color represents a distinct run with the same punishment probability p=0.25

Tests using a combination of asynchronous activation mechanisms, show that populations affected by players who activate randomly, are unable to maintain stability over long periods of time. For various runs of the game with the same value of p the outcome of the game changes. Simulations show that different runs lead to different results. This particular method of activation does not provide consistent results over multiple runs of the game.

2.5. **World Dynamics Using the Cyclic Schema.** Fig. 10a, 10b, 10c, 10d, 10e, 10f, 10g, 10h reveal the dynamics of the world activation using the Cyclic schema. We use two different values for N and four different values of p for each value of N. We run experiments for 200.000 rounds and four different

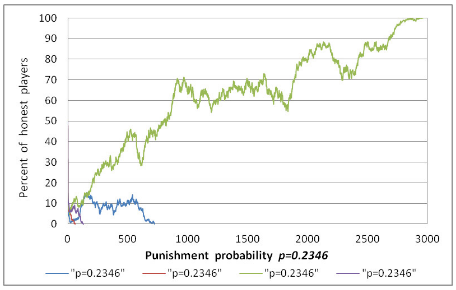

Fig.10a.Activation using the Cyclic schema (N=100, p=0.2346). Each color represents a different run with the same punishment probability p=0.2346

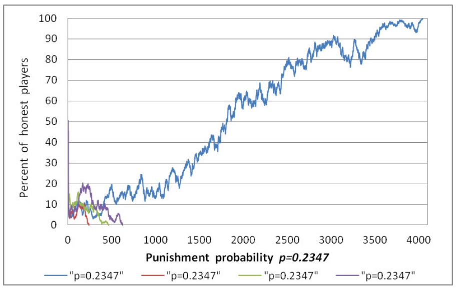

Fig.10b.Activation using the Cyclic schema (N=100, p=0.2347). Each color represents a different run with the same punishment probability p=0.2347

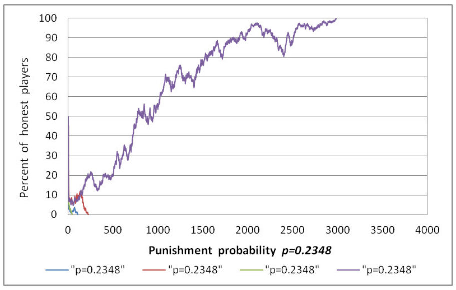

Fig.10c.Activation using the Cyclic schema (N=100, p=0.2348).Each color represents a different run with the same punishment probability p=0.2348

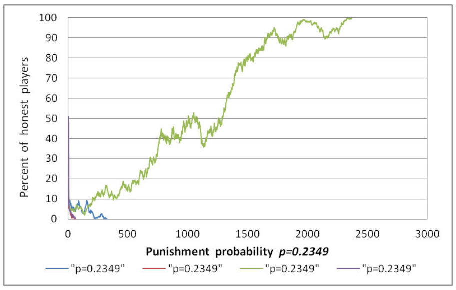

Fig.10d.Activation using the Cyclic schema (N=100, p=0.2349).Each color represents a different run with the same punishment probability p=0.2349

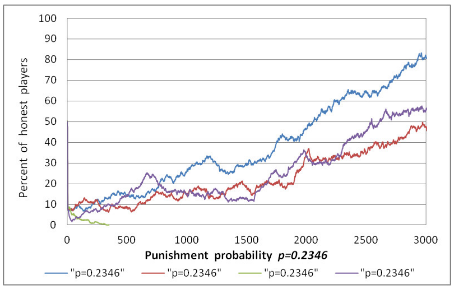

Fig.10e.Activation using the Cyclic schema (N=200, p=0.2346).Each color represents a different run with the same punishment probability p=0.2346

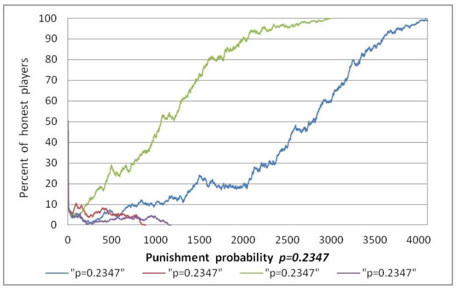

Fig.10f.Activation using the Cyclic schema (N=200, p=0.2347).Each color represents a different run with the same punishment probability p=0.2347

runs for each value of p. Each colored graph represents a different run of the game with the same value of p.

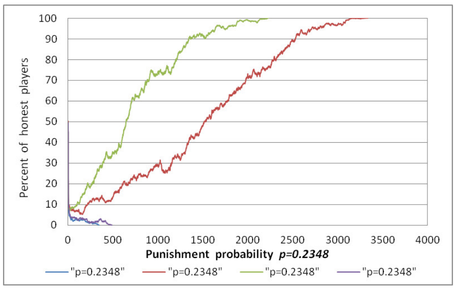

Fig.10g.Activation using the Cyclic schema (N=200, p=0.2348).Each color represents a different run with the same punishment probability p=0.2348

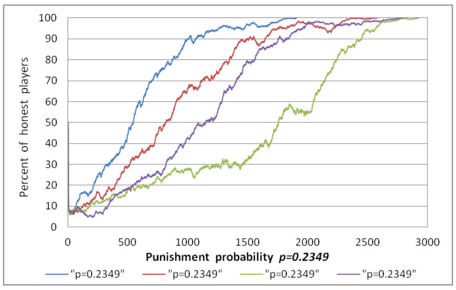

Fig.10h.Activation using the Cyclic schema (N=200, p=0.2349).Each color represents a different run with the same punishment probability p=0.2349

Clusters of honest players emerge from the beginning of the game, but this schema of activation does not ensure stability in time for various runs of the same values of p. A dynamic equilibrium cannot be established for longer periods of time using the cyclic schema.

When players do not act synchronously the clusters need a longer time to form, regardless the mechanism used. Asynchronous activation causes a rich dynamical behavior. In real world complex systems, synchronous or random asynchronous activation are rare. Natural complex systems activate somewhere between. One suitable example is the clock or the cyclic schema. Time is a very important reference position, since people tend to organize their lives according to different moments in their lives (i.e. birthday, sunrise, dawn, time for going to work, time for lunch etc).

3. Asynchronism in biological systems

Existing research using asynchronous models of activation in cellular automata based computer simulations and classical "game of life"[14] reveal rich dynamical behaviors in complex systems found in nature and social interactions.

Biological systems provide evidence that players update their states according to a wide variety of updating schemes. Simulations of the synchronous and self-synchronous schemes in spatial evolutionary games [8] reveal complex patterns not seen in the Clock and Random schemes. All the updating schemes used in the simulations were able to create "gliders" (agents that randomly walk across the lattice). Due to the fact that the lattice has fixed margins the "gliders" are lost and the system converges to a fixed state. Asynchronous schemes of activation led to emergence complicated dynamical features, not seen in the synchronous counterparts. The results obtained show that populations that were able to keep a stable rate of cooperators, using synchronous activation, were unable to do so using asynchronous methods of activation.

A different approach towards human interactions using asynchronous player activation in "prisoner's dilemma" is proposed in [17]. A reputation-based migration model leads to the emergence and persistence of cooperation. However punishment (P) is only used in mutual defection. In case of D-C interaction (D-defector, C-cooperator), the cooperator gets a sucker's payoff while there is no probability of punishment for defector, only a temptation T to defect. Reputation memory length determines the level of cooperation.

Asynchronous activation in the "game of life" [12] using a probability s for updating each site of the lattice reveals a critical phase transition. For s=1 we have the classical "game of life". As s decreases down to 0, the steady-state is characterized by domains of alternating dead and live stripes. The final equilibrium and the time needed to equilibrate depends of the initial density.

Real complex systems lie somewhere between synchronous activation and random asynchronous activation. In [2] a new type of activation was proposed by authors Asynchronous Stochastic Dynamics (ASD). Experiments reveal that lower values of the synchrony rate become more beneficial to the evolution of cooperation. The conclusions extrapolated from the simulations lead to the assumption that the lower the value of the m parameter, the more is cooperation favored when we decrease the value of α (where the m parameter acts as a weight that favors the most successful neighbor's strategy B in the update process: the bigger the m the larger is the probability that an agent adopts the strategy B, and α is the probability of an agent interacting with its neighbors).

Studies made thus far [3] show that in general, asynchronism allows the emergence of a bigger fraction of cooperators in the Spatial Prisoner's Dilemma game than synchronism. The state of every agent is updated according to the highest payoff as a result of interacting with its neighbors. Two different update disciplines were used, stochastic and deterministic periodic updating, in order to determine how the players rate changes in the Prisoners Dilemma game. When ASD is used, at each time step, each agent has a given probability 0 ¡ α 1 of applying the transition rule in order to decide which strategy to use next. The α parameter is called the synchrony rate and is the same for all agents. When $\alpha = 1$ we have synchronous updating and as $\alpha \to 1/\mathrm{n}$, where n is the population size, ASD approaches sequential updating.

Compared to existing results [8], in Social Honesty game honest players were able to survive for long periods of time and coexist with dishonest players using the Cock schema and proper values of p. The transition intervals are changing, therefore we have an effect of asynchronism that favors a dishonest strategy for lower values of p.

In Social Honesty we use a punishment probability p as a dishonest behavior deterrence mechanism, instead of a temptation (T) [17] to defect. Using a asynchronous method of activation, simulations show that in the presence of reputation-based migration [17], ω_c (fraction of cooperators) is promoted for a low temptation to defect, thus cooperation can be enhanced.

In Social Honesty game the dynamic equilibrium between honest players and dishonest players depends of the value of p used in simulations and the method of updating used. We used in simulations a probability p_r for a player to activate according to the Random Order schema. A similar approach we find using the probability s [12] for updating each site of the lattice. However in our study the Random Order schema did not provide a dynamic equilibrium between honest and dishonest players for longer periods of time unlike the ASD [2, 3] updating mechanism used.

4. Conclusions

Previous studies of synchronous activation of players, reveal cluster formation from the beginning of the game. Lower values of p are needed for H-players to coexist with D-players.

When players do not act synchronously, honest players tend to organize themselves into greater clusters, rather than more small clusters (see Fig.7). Comparisons between synchronous and asynchronous activation reveal that asynchronous player activation leads to unexpected results in the players percent rate. When players have less options for imitation, due to the asynchronous activation mechanisms, larger fluctuations appear in the number of H-players (see fig. 5a, 5b, 7, 8a, 8b, 9a, 9b, 9c, 9d, 9e, 9f).

Clusters of honest players need a longer time to form, using asynchronous activation mechanisms (see fig. 6 and 7). Optimal punishment probability becomes more difficult to find, due to the greater fluctuations in players percent rate (see fig. 2a, 2b, 3a, 3b). D-players tend to organize themselves into cluster similar to H-players.

A few differences are to be noticed between the different schemes of activation. Compared to the other methods of asynchronous activation, the Clock schema proved to be the most stable in the game. The transition interval for the Clock schema is significantly larger than other mechanisms of activation, except the combination of the methods used in this game.

The Random Order Schema and the Cyclic schema do not provide a balance between H-players and D-players over longer periods of time. All players become either honest or dishonest. When players activate according to the Random Order schema, repeated runs of the game with the same values of p lead to the same outcome (honest players win with a particular value of p, regardless the number of repetitions). It is not the case with the Cyclic schema of activation, where for repeated runs with the same value of p the outcome is different (with the same value of p used for repeated runs, the game leads to different outcomes, (i) honest players win or (ii) become extinct).

The combination of the two schemes proves to be the most intriguing. We were unable to establish consistent results over repeated runs of the game. As seen in fig. 9a, 9b, 9c, 9d, 9e, 9f for various runs there are three possible outcomes of the games: (i) the honest players win, (ii) the honest players become extinct and (iii) a balance was actually possible for a longer time. Results were not consistent.

The Social Honesty game analyses human interaction and the way players react to different values of punishment probability. It has been proved that punishment probability is more important than punishment severity [9], therefore we use results from the transition interval in order to find the optimal values of punishment probability since a "zero tolerance" policy [15] had been proved to be too costly.

Using a proper punishment probability, economical and even political stability can be achieved as a result of a stable percentage of honest players. Transition intervals can very well be manipulated by law makers and leaders with overall benefits for society. Proper values of punishment probability can be effectively used by decision makers. The model we propose takes into consideration that there will always be an incentive towards dishonest behavior.

Law makers and society leaders are influenced by policy makers [5]. Unless the decisions made by the first, are not scientifically grounded, there will always be a risk not to have the anticipated results and measures can be ineffective. However an improper argumentation of any measure, regardless of the fact that it was very carefully analyzed from a scientifically approach, will lead to a failure in becoming a long term strategy. As future work we intend to experiment new scenarios that combine asynchronous updating with other parameters (i.e. other topologies, learning rules, etc.).

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