Vet On-Line

Agent Based Simulation in Biology: the Case of Periodical Insects as Natural Prime Numbers Generators

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ABSTRACT

Magicicada is the genus of the 13 and 17 year periodical cicadas of eastern North America; these insects display a unique combination of long life cycles, periodicity, and mass emergences. Their nymphs live underground and stay immobile before constructing an exit tunnel in the spring of their 13th or 17th year, depending on the species. Once out, the adult insects live only for a few weeks with one sole purpose: reproduction. Both 13 and 17 are prime numbers; why did the cicadas "choose" these lengths for their life cycles? One interesting hypothesis is that the prime number cycles were selected because they were least likely to emerge with other cycles. If that's the case, then these lengths would have been selected via a sort of "tacit communication" by evolution. In the present work we create an agent based model, depicting a world in which cicadas with different life cycles go outside and cross among them, creating other insects with a life cycle inherited from the parents. In the simulation food is limited and predators exist, that can be satiated if the number of cicadas going out is large enough. The model could give us an empirical answer to the following question: is the "predator satiation" hypothesis enough, along with the limited food quantity, to explain the prime numbers based life cycle of these insects?

1. Introduction

There are two species of cicada, called *Magicicada Septendecim* and *Magicicada Tredecim*, which have a life cyle of 17 and 13 years respectively (Remondino, 2005). These are among the longest living insects in the world; they display a unique living behaviour, since they remain in the ground for all but their last few weeks of life, when they emerge "en masse" from the ground into the forest where they sing, mate, eat, lay eggs and then die. The nymphs of the periodical cicadas live underground, at depths of 30 cm (one foot) or more, feeding on the juices of plant roots. They stay immobile and go through five development stages before constructing an exit tunnel in the spring of their 13th or 17th year. Adult periodical cicadas live only for a few weeks: by mid-July, they will all be gone. Their short life has one sole purpose: reproduction. After mating, the male weakens and dies. The female lives a little longer in order to lay eggs: it makes between six and 20 V-shaped slits in the bark of young twigs and deposits up to 600 eggs there. Shortly afterwards, the female also dies. After about six to ten weeks, the eggs hatch and the newborn nymphs drop to the ground, where they burrow and begin another 13 or 17 year cycle.

The fact that they have both evolved prime number life cycles is thought to be key to their survival. Many are the hypothesis about why these insects display these life cycle lengths. Two are the most interesting ones, and both of them require an adaptation by evolution of these species. The first one is about limited resources, that must be shared by the insects once out. By evolving life cycles of 17 and 13 years, the two species only have to share the forest floor every 221 years, that's 13 times 17. Resource boundedness can then be considered as an upper limit for the cicadas: no more than a threshold could survive with the available food, and then the fewer insects are out at the same time, the better.

The second hypothesis, actually interacting with the first one, is somewhat opposite to it; it's called *predator satiation hypothesis* and moves the focus from the insects to their main predators: dogs, cats, birds, squirrels, deer, raccoons, mice, ants, wasps, and even humans make a meal of the cicadas. Predator satiation is when a species can survive because its abundance is so great that predators do not have a large enough impact to effect the species' survival. In order to prove that predator satiation is occurring in a certain situation one must prove that above a certain prey density, the frequency of predation does not increase as the prey density increases (Williams et al.,1993). In the case of magicicadas this has been proven to occur. When the first cicadas emerge from the soil there is a very high predation rate, especially from avian predators. However, the predation rates decline over the next couple of days as predators have indulged in all the food they needed, or "satiated". Then, by the time that the satiation of the predators has worn off and foraging activities increase again, the density of adult cicada's has begun declining and they have already mated. This creates a situation where only a small portion of the adult population is consumed by predators. This is indeed a sort of lower bound for the number of cicadas that can be out at the same time; in few words, the more cicadas out at the same time, the least the possibility of being decimated by predators. Also according to this hypothesis, the prime numbers have a motivation: the prime number cycles were selected for because they were least likely to emerge with other cycles. For periodical cicadas emerging with other cycles of cicadas would mean hybridization, which would split up populations, shift adult emergences, and create lower densities below the critical size (Yoshimura, 1996). This would have made it harder for the hybridized broods to survive predation. Thus, prime number cycles which emerged with other cycles the least, would grow in population size over time because they would have the highest survival rates.

Considering these two hypothesis as real and founded, then we can assume that there has been a sort of selection among the species through many generations or, better a "tacit communication by evolution". In this way, the prime number cycles can be seen a very interesting emergent natural phenomenon, where the conclusions (results) were not embedded in any way into the initial data. For this reason, we chose to model this phenomenon using Agent Based Simulation (ABS), a tool allowing us to capture emergent behaviour arising from complex systems. Using an agent-based model of the cicadas' life cycle, we simplify the world in which they life and reduce it to just few parameters, essentially the limited resources and the predators. The cicadas have an reproduction rate, and so the predators and the food; we wonder if these parameters are enough for prime number life cycles to emerge.

2. Agent Based Simulation and Emergent Behaviour

In the study of aggregate behaviour within Biology, it is more and more recognized that in addition to real experiments and field studies, also simulation experiments are a useful source of knowledge and verification. Using simulations for testing and validation of computational models could be seen as performing an experiment: since in the social sciences real experiments are in many cases not possible or only in a very restricted way, the use of computer simulations plays a decisive role: very often computer experiments have to play the part of real experiments in the laboratory sciences. By the way, that is also the case in those natural sciences where for similar reasons experiments are not (yet) possible, in particular in the those sciences like Entomology or evolutionary Biology.

ABS looks at agent behaviour at a decentralized level, at the level of the individual agent, in order to explain the dynamic behaviour of the system at the macro-level. Instead of creating a simple mathematical model, the underlying model is based on a system comprised of various interacting agents. Therefore, its structure and behaviour have potential to resemble the actual economic theory and reality better than simple mathematical models. Especially, when the underlying real relationships are complex. There are many accepted definition for the word "complexity", when applied to a social system, i.e.: a system in which the single parts interact among them. The first and most straightforward one is the following (Pavard and Dugdale, 2000):

A complex system is a system for which it is difficult, if not impossible to restrict its description to a limited number of parameters or characterizing variables without losing its essential global functional properties.

Formally, a system starts to have complex behaviours (non-predictability and emergence etc.) the moment it consists of parts interacting in a non-linear fashion. According to this, a complex system is defined as:

…the interaction of many parts, giving rise to difficulties in linear or reductionist analysis due to the nonlinearity of circular causation and feedback effects (Calresco Glossary).

It is thus appropriate to differentiate between a complicated system (such as a plane or computer) and a complex system (such as ecological or economic systems). The former are composed of many functionally distinct parts but are in fact predictable, whereas the latter interact non-linearly with their environment and their components have properties of self-organization which make them non-predictable beyond a certain temporal window.

A truly complex system would be completely irreducible. This means that it would be impossible to derive a model from this system (i.e. a representation simpler than reality) without losing all its relevant properties. However, in reality different levels of complexity obviously exist. If we are interested in situations which are highly structured and governed by stable laws, then it is possible, without loosing too many of the system's properties, to represent and model the system by simplification. Thus, the essential question is to know to what extent the properties of the social systems that we analyze and design fall into one or the other of these situations. In other words, to what extent we can make an abstraction of microscopic interactions in order to understand macroscopic behaviours. In what measure microscopic interactions are linked in a non-reducible way with the laws that govern more structured behaviours and, finally, we must check if it is possible to explain the most structured behaviour using rules which control the microscopic behaviour. This last question is important from an epistemological and methodological point of view: if we consider theoretical economy, it can be preferable to generate the structural property of a system using knowledge of its microscopic properties (emergence), rather than suggest its macroscopic properties and only validate them with an analytical process.

The reduction of complexity is an essential stage in the traditional scientific and experimental methodology (also known as analytic). After reducing the number of variables (deemed most relevant), this approach allows systems to be studied in a controlled way, i.e. with the necessary replication of results.

As stated before, we are facing a situation in which an emergent behaviour occurs: prime number life cycles are probably a result of the environment in which the cicadas live. The agent-based model could give us an empirical answer to the following question: is the "predator satiation" hypothesis enough, along with the limited food quantity, to explain the prime numbers based life cycle of these insects?

3. Different Kinds of Agents

The term agent, deriving from the Latin “agens”, identifies someone (or something) who acts; the same word can also be used to define a mean through which some action is made or caused. The term is used in many different fields and disciplines, such as economics, physics, natural sciences, sociology and many others. In computer science, the word is used to define very heterogeneous entities and sometimes is even abused. The main purpose of this work is to investigate various kinds of software agents that could be applied to modeling and simulation of complex social systems. In this paragraph we will review different kinds of agents, in order to select the ones which best fits for our purpose.

The concept of software agent originates in the early fifties with J. McCarthy, while the term has been coined by O.G. Selfridge some years later, when both of them were working at the Massachusetts Institute of Technology. Their original project was to build a system which, given a goal, could be able to accomplish it, looking for human help in case of lack of necessary information. In practice, an agent was considered a software robot that lives and acts in a virtual world. In (Wooldridge and Jennings 1995): "... a hardware or (more usually) software-based computer system that enjoys the following properties:

- autonomy: agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state;
- social ability: agents interact with other agents (and possibly humans) via some kind of agent-communication language;
- reactivity: agents perceive their environment, (which may be the physical world, a user via a graphical user interface, a collection of other agents, the internet, or perhaps all of these combined), and respond in a timely fashion to changes that occur in it;
- pro-activeness: agents do not simply act in response to their environment, they are able to exhibit goal-directed behaviour by taking the initiative." The Wooldridge and Jennings definition, in addition to spelling out autonomy, sensing and acting, allows for a broad, but finite, range of environments. They further add a communications requirement.

Franklin and Graesser (1997) also try to find the typical features of agency, deriving them from the word itself: an “agent” is 1) one who acts, or who can act, and 2) one who acts in place of another with his permission. Since "one who acts in place of " acts, the second usage requires the first. Humans act, as do most other animals. Also, some autonomous mobile robots act, for example Brooks' Herbert (Brooks 1990; Franklin 1995). All of these are real world agents. Software agents "live" in computer operating systems, databases, networks, MUDs, etc.

Finally, artificial life agents "live" in artificial environments on a computer screen or in its memory (Langton 1989, Franklin 1995).

Each is situated in, and is a part on some environment. Each senses its environment and act autonomously upon it. No other entity is required to feed it input, or to interpret and use its output. Each acts in pursuit of it's own agenda, whether satisfying evolved drives as in humans and animals, or pursuing goals designed in by some other agent, as in software agents. (Artificial life agents may be of either variety.) Each acts so that its current actions may effect its later sensing, that is its actions effect its environment. Finally, each acts continually over some period of time. A software agent, once invoked, typically runs until it decides not to. An artificial life agent often runs until it's eaten or otherwise dies. Of course, some human can pull the plug, but not always. Mobile agents on the Internet may be beyond calling back by the user.

These requirements constitute for sure the essence of being an agent, hence the definition by Franklin and Graesser (1997):

An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future.

And the very general, yet comprehensive one by Jennings (1996):

…the term is usually applied to describe self-contained programs which can control their own actions based on their perceptions of their operating environment.

Agents themselves have traditionally been categorized into one of the following types (Woolridge and Jennings, 1995):

- Reactive

- Collaborative/Deliberative
- Hybrid

When designing any agent-based system, it is important to determine how sophisticated the agents' reasoning will be. Reactive agents simply retrieve pre-set behaviors similar to reflexes without maintaining any internal state. On the other hand, deliberative agents behave more like they are thinking, by searching through a space of behaviors, maintaining internal state, and predicting the effects of actions. Although the line between reactive and deliberative agents can be somewhat blurry, an agent with no internal state is certainly reactive, and one which bases its actions on the predicted actions of other agents is deliberative.

In Mataric (1995) we read that reactive agents maintain no internal model of how to predict future states of the world. They choose actions by using the current world state as an index into a table of actions, where the indexing function's purpose is to map known situations to appropriate actions. These types of agents are sufficient for limited environments where every possible situation can be mapped to an action or set of actions.

The purely reactive agent's major drawback is its lack of adaptability. This type of agent cannot generate an appropriate plan if the current world state was not considered a priori. In domains that cannot be completely mapped, using reactive agents can be too restrictive.

Different from reactive agents are the deliberative ones. The key component of a deliberative agent is a central reasoning system (Ginsberg, 1989) that constitutes the intelligence of the agent. Deliberative agents generate plans to accomplish their goals. A world model may be used in a deliberative agent, increasing the agent's ability to generate a plan that is successful in achieving its goals even in unforeseen situations. This ability to adapt is desirable in a dynamic environment.

The main problem with a purely deliberative agent when dealing with real-time systems is reaction time. For simple, well known situations, reasoning may not be required at all. In some real-time domains, such as robotic soccer, minimizing the latency between changes in world state and reactions is important.

Hybrid agents, when designed correctly, use both approaches to get the best properties of each (Bensaid and Mathieu, 1997). Specifically, hybrid agents aim to have the quick response time of reactive agents for well known situations, yet also have the ability to generate new plans for unforeseen situations.

A multi agent system can be thought of as a group of interacting agents working together to achieve a set of goals. To maximize the efficiency of the system, each agent must be able to reason about other agents' actions in addition to its own. A dynamic and unpredictable environment creates a need for an agent to employ flexible strategies. The more flexible the strategies however, the more difficult it becomes to predict what the other agents are going to do. For this reason, coordination mechanisms have been developed to help the agents interact when performing complex actions requiring teamwork. These mechanisms must ensure that the plans of individual agents do not conflict, while guiding the agents in pursuit of the goals of the system.

For our purposes, the agents which seem most suited are the reactive ones. We need agents able to react to simple stimuli coming from the environment – the insects, the predators and food. Everything in our model will be designed as an agent, but a very simple one.

4. Analytical and Simulation Modelling

Modeling is a way of solving problems that occur in the real world. It is applied when prototyping or experimenting with the real system is expensive or impossible. Modeling allows to optimize systems prior to implementation. It includes the process of mapping the problem from the real world to its model in the world of models, – the process of abstraction, – model analysis and optimization, and mapping the solution back to the real system. We can distinguish between analytical and simulation models. In analytical, or static, model the result functionally depends on the input (a number of parameters); it is possible to implement such model in a spreadsheet.

However, analytical solution does not always exist, or may be very hard to find. Then simulation, or dynamic, modeling may be applied. A simulation model may be considered as a set of rules (e.g. equations, flowcharts, state machines, cellular automata) that define how the system being modeled will change in the future, given its present state. Simulation is the process of model "execution" that takes the model through (discrete or continuous) state changes over time. In general, for complex problems where time dynamics is important, simulation modeling is a better answer. In Figure 1, metaphor based approach (Remondino, 2003) is shown, depicting how to step from a real observed situation (problem in the real world) to a computer model and hence to a simulation in order to obtain results that can be scaled back to be applied to the original problem.

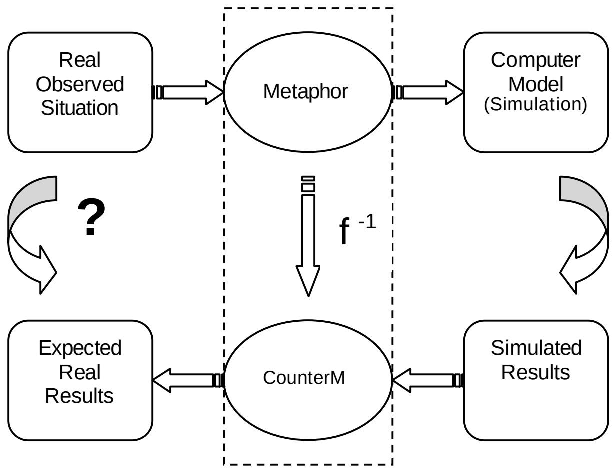

Fig. 1 From the real world to the simulation

The metaphor layer is a conversion one, and works like a function, which maps a real situation onto a computer program, that can be executed by a machine. The results obtained by the simulation built with this approach, don't necessarily apply one-to-one to the real situation.

Therefore, an inverse function is required, which makes them suitable for the observed reality; this inverse function, called counter-metaphor, has to be directly derived from the metaphor used to port the observed system into the simulated model. This counter-metaphor will allow going back from the results obtained from the model to others that can be compared to the real data.

According to (Troitzsch, 1996), computer simulation in the social sciences has at least two types of origins: on one hand, it continues mathematical modeling and is no more than the numerical treatment of difference equations or the various kinds of differential equations (including partial and stochastic differential equations). Here, a machine is used to manipulate the symbols of the symbol system of mathematics, and this manipulation is more or less restricted to numerical treatment (although some computer help in symbolic computation is sometimes desirable, too). On the other hand, computer simulation is used in its own right, not as a substitution for more elegant mathematical solution algorithms, but as a means of manipulating the symbols of the symbol system of programming languages.

Ostrom (1988) described simulation as a third symbol system in its own right and as an alternative to mathematical formalization of social science theories and verbal argumentation. The former is of course highly computable, but it's very difficult to express real observed situations just by numerical means and equations. The other alternative is natural language, which has a huge capability in representation but it's not computable at all. Ostrom stated that "any theory that can be expressed in either of the first two symbol systems can also be expressed in the third symbol system" and that computer simulation has the advantages of both the other symbol systems, without their disadvantages, since it "can be used for representing both qualitative, natural language constructs and quantitative, mathematical constructs".

The first use of simulation is to detect which conclusions may be drawn from complex antecedents. This is what used to be called concept-driven simulation (Henize, 1984). A target system is represented by a verbal, mathematical, or computer model (with all the necessary simplifications). The question is about the possible futures of such a target system: will it stabilize overtime or be destabilized? What happens if we change something in the initial conditions? Can the system be optimized, regarding some core parameters? This is the core of the simulation process, sometimes referred to as what if analysis; a simulation can indeed give some very useful results about what we can expect from the target system, when this is carefully modeled. Of course simplifications are needed – a model, by definition, is a scaled down representation of reality – but even then the results can apply to real situations.

5. The model

We created an agent based model using the JAS library (http://jaslibrary.sourceforge.net/), in order to simulate different situations in which many species of cicadas compete for finite resources and are threatened by some predators. The only difference among the species, in our model, is the duration of their life cycle; population #1 will have a one year long life cycle, while population #20 a twenty years life cycle and so on. In this paragraph we describe the model as it's been implemented; we put in *italic* the variable name.

We define a world with a fixed amount of resources (*resources*), that can be consumed by cicadas, a fixed amount of predators (*predatorsNumber*) and a probability to survive at wake up (*chanceToSurviveAtBirthRate*). Except for the costrain represented by food (*resources*), the other (*chanceToSurviveAtBirth* and *predators*) can be switched on and off, through the parameters window.

The population of cicadas is characterized by the number of members (*magicicadasNumber*), randomly distribuited among the different classes and by a growth rate (*reproductionRate*).

We use a fixed number of predators in order to underline that their population is not influenced by cicadas; In fact these insects represent only an alternative food, among the many present in nature.

At the beginning of the simulation the cicadas are uniformly randomly distributed among *C* classes/sub-species. In our metaphorical world, each class of cicadas has a different life cycle length, so that they wait a different number of years underground, from a minimum of 1 to *maxSleepingTime*. We decided to use 20 as a maximum number of years a cicada can live, since in nature the *magicicada septendecim* is already the longest living insect, and we wanted to have a realistic setup. However, our model supports whatever number as a maximum life cycle.

At each simulation step, one year passes. At any turn the model inquires every cicada in order to update/reduce the number of years left for it to stay underground, or if this time is over, wake it up.

The probability *chanceToSurviveAtBirthRate* also increases every year they spent underground. This is done according the biological theory that a longer life cycle is usually a good achievement. In particular, for the cicadas, Yoshimura (1996) points out that during the climate cooling of the Glacial period, growth and development of cicada nymphs was slowed down by lowering soil temperature. He supports this by pointing out that it is well known that cumulative temperature is very critical in insect development. Also, the fact that the cooling climate slowed down the development of host plants from which cicadas get their nutrient may have also slowed their development. Because cicadas needed proper nutrients at each stage of their developmental cycle, and they were provided less because of the cooling temperatures, their life cycle was extended to larger range of years. So in the model we increase the *chanceToSurviveAtBirthRate* at any simulation step, to reproduce this natural phenomenon. When the cicadas have to go outside (i.e.: when their time underground is over), they perform a first check according to this probability.

As soon as they go outside, the cicadas must eat and reproduce themselves. Since the resources are limited, in our model only a certain number of cicadas can survive at each year/tic; this is a strong constraint existing also in the real world. We decided that if there are *n* resources in the world, at time *t*, only *n* cicadas will survive.

Then predators can also eat cicadas, and reduce the population. This is the second constraint, present in the real world. In order to fulfil the “predator satiation” hypothesis we decided that after eating a fixed number of cicadas, the predators are satiated and let the other cicadas live and reproduce.

Finally the survived cicadas can reproduce and die; we clone the cicadas according to *reproductionRate*: the new cicadas have the same properties of their parents, and start a new life cycle underground, according to their duration.

Obviously, before each step we shuffle the list of alive cicadas, in order to randomise the process.

6. Results

Here we present some of the results from the simulation. Each run represent 20.000 years of time, in which we compute each step presented before, in order to define the population dynamics. For each run we show the graphs at times 20, 1000, 5000 and 20000.

Each graph has on x axis the classes, ordered by the number of years to be spent underground before emerging to the surface; on y axis the number of cicadas.

The first run we present features these parameters:

magicicadasNumber	10000
reproductionRate	6.0
chanceToSurviveAtBirth	true
chanceToSurviveAtBirthRate	0.15
predators	true
predatorsNumber	190
resources	1000
maxSleepingTime	20

During first 20 steps (figure 2) the cicadas with few years of sleeping died, according to their low *chanceToSurviveAtBirthRate*. At this time nothing can be said about the trend, yet, since most of the cicadas have been out for just one time and the food and predators dynamics have not yet influenced the results.

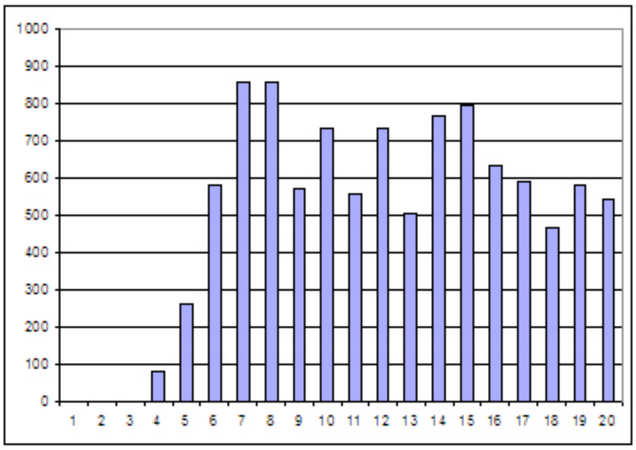

Fig. 2 Experiment 1 at 20 tics

Normally the even classes are the least likely to survive, since they have many divisors. This causes many cicadas to be out at the same time, that starve to death according to the limited resources constraint. As you can observe in figure 3, all the even classes are gone, but class #20. This is because it’s the longer living one (and in our model “longer is better”) and because it’s out less then others. Notice that at this time (after 1000 years) four out of six classes which still exist have a prime number based life cycle.

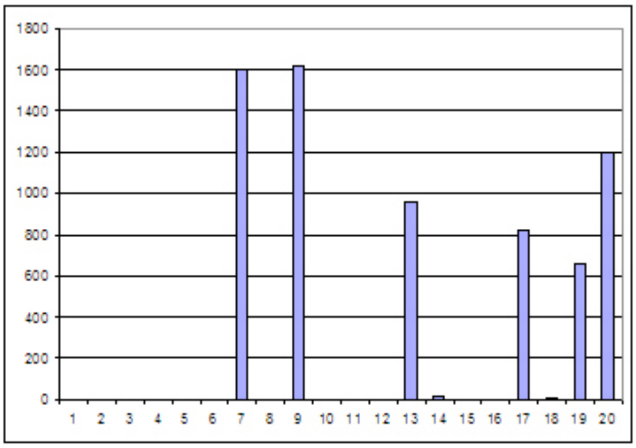

Fig. 3 Experiment 1 at 1000 tics

Without the *chanceToSurviveAtBirthRate*, which increases at each time step the probability of a class to survive and go out, we’d obtain a different effect: in fact the populations with longest sleeping time are not competitive as the others, since they don’t take advantage from the reproduction rate, being out less often. This would be highly unrealistic: the classes with a short life cycle (one to three years) will have much more chances to go out and reproduce themselves, when compared to those with longer cycles. As said before, nature often prefers longer life cycles, when possible, so our model holds.

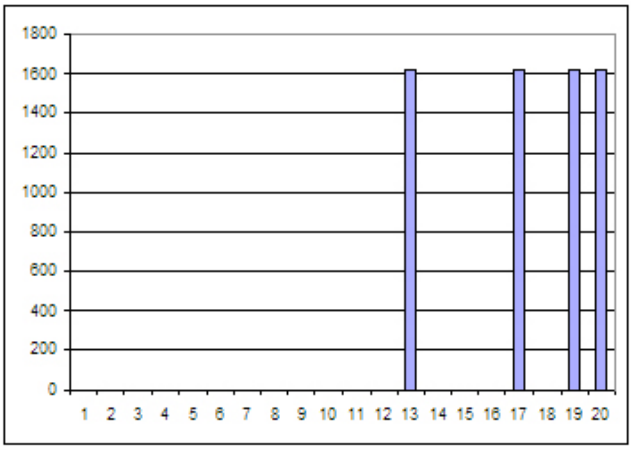

Fig. 4 Experiment 1 at 5000 tics

In figures 4 and 5 we can observe the typical trend of all the experiments, with a stable population concentrated in few classes. In particular, with the parameters we choose, after 5000 tics we have three high prime numbers (13, 17 and 19) and the longest possible class (20), while after 20000 cycles the highest reproduction rate of the lower classes wins over the longest living one, and the only three remaining are represented by the three highest prime numbers lower than 20, which are 19, 17 and 13. While in nature a cicada with a life cycle of 19 years doesn't exist, probably because it wouldn't be possible for such insect to life so long, in our simulated world that is considered feasible. If we had classes just up to 18, we would have reproduced exactly the real situation, that is one in which two species emerge, the *magicicada tredecim* and the *magicicada septendecim*. In this experiment, then, you can observe that the populations of magicicadas confirm the "myth" of being biological prime number generator.

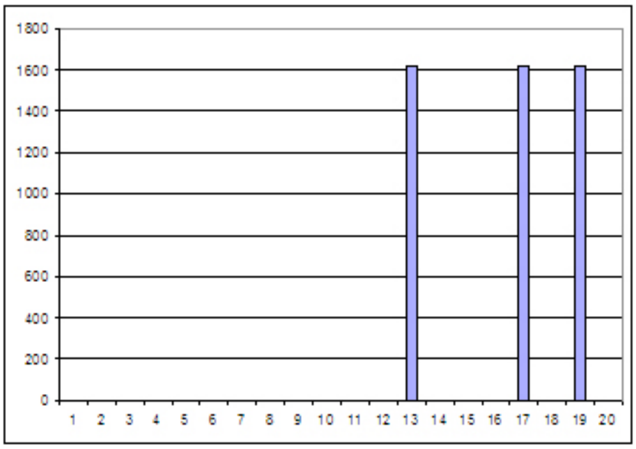

Fig. 5 Experiment 1 at 20000 tics

We present also another run with few different parameters, which are shown below:

magicicadasNumber	10000
reproductionRate	2.0
chanceToSurviveAtBirth	true
chanceToSurviveAtBirthRate	0.1
predators	true
predatorsNumber	180
resources	1000
maxSleepingTime	20

As you can see, we lowered the reproduction rate, from 6.0 to 2.0, and we also lowered the "chance to survive at birth rate", from 0.15 to 0.1. Also the predators number is lower, stepping from 190 to 180. This set of parameters should penalize the two extremes: shortest living classes have less benefits from the reproduction rate, which is lower, while longest living ones don't tale advantage from living underground as in the previous experiment.

The initial steps (fig. 6) are very similar to experiment 1, with some relevant differences: class #4 and #5, which in the first experiment had about 100 and 250 cicadas, respectively, are now almost gone after the first 20 steps.

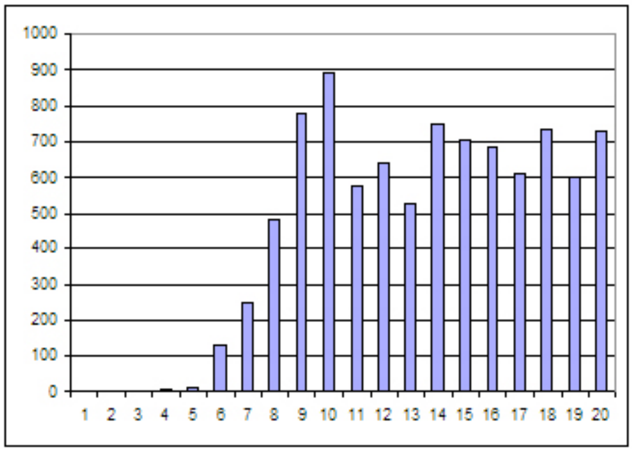

Fig. 6 Experiment 2 at 20 tics

A lower reproduction rate affects the shortest living classes in the longer runs, while a lower probability to survive being underground for longer times affects the highest one, as you can see in figure 7. This figure will be even more evident when reach a steady state at turn 5000. After 1000 years four out of seven classes are prime numbers.

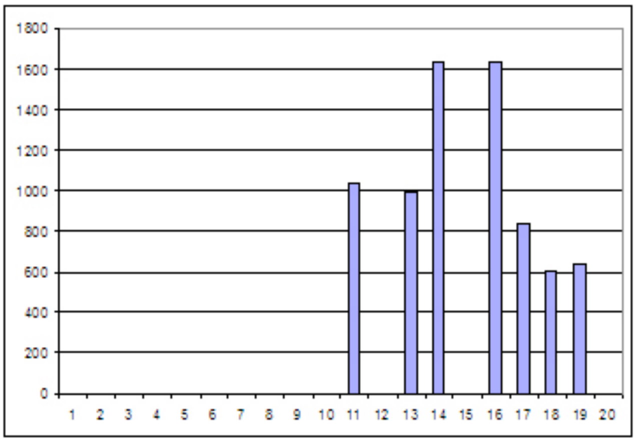

Fig. 7 Experiment 2 at 1000 tics

After 5000 tics (figure 8) the situation is clear and prefigures the final one at 20000 tics (figure 9). Class #11 is the lowest which survived the selection, while #17 is the highest among the three which are still alive. This proves that the results are quite "parameters sensitive" and that, again, this model is a good prime numbers generator. But here we also have class #14; even if its trend is a decrease, going from 5000 to 20000 steps, we think that it survived since it's a central class among the other two and, above all, 14, even being an even number, is the only one left in the model so doesn't have to concur with others. If we run the simulation for other 20000 years or so we probably would have found a world with just classes #11 and #17 in it.

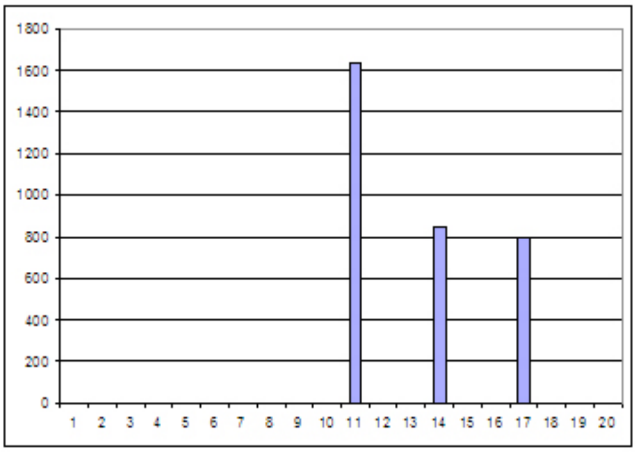

Fig. 8 Experiment 2 at 5000 tics

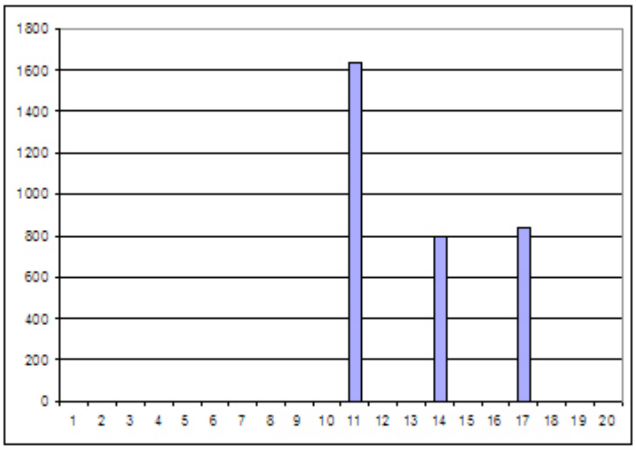

Fig. 9 Experiment 2 at 20000 tics

The results are quite interesting since in two different runs, with different parameters, the classes which are most likely to survive are those based on prime numbers, but cicadas don't know prime numbers and can't even calculate! This is a good example about how agent based models can show an emergent behaviour, just from the interaction of many simple entities, even when the agents are not "intelligent" at all, but just reactive agents responding to the stimuli coming from the environment.

7. Parameters Tuning by Repeated Execution

Our model, for its construction, is very "parameters sensitive", in the sense that a slightly different reproduction rate, or a negligible variation of the cicadas/predators ratio can lead to very different results in the long run. For this reason, we thought of a way to test many different parameters using a sort of "brute force" approach, i.e. by changing a value at a time, the others being the same (ceteris paribus). This is a sort of tuning, of even validation, useful to select the parameters that best fit the real situation. This is done mainly for two reasons:

1) find dependencies among parameters and results
2) being able, once found the "best" parameters to get prime numbers, to start what-if analysis and simulate situations different from the real ones.

In particular, we want to see what happens if the species are 50, instead of 20. This is something which is, of course, impossible in reality, where a cicada living 17 years is already the longest living insect in the world, but could be very interesting to simulate, in order to see if this can be a true "prime numbers biological generator".

8. CONCLUSIONS

Biology is an important reference for agent based modelling, both as a source for examples/applications and as methodological inspiration. Many important results in Artificial Life and Computer Science are based on biological metaphors such as the *ALife* concept itself and, in detail *Game of Life* by John Conway, Holland's *Genetic Algorithms*, *Neural Networks* and many others. We also mention the simple ants or "vants" (*virtual ants*), with their simple rules and their simulated pheromones that are present in a great number of models and algorithms, since the Langton's ant.

In this paper we applied agent based simulation to a biological phenomenon. Two species of cicadas living in North America show a unique behaviour: they remain in the ground for all but their last few weeks of life, when they emerge "en masse" from the ground into the forest where they sing, mate, eat, lay eggs and then die. The most interesting part is that their life cycle is, respectively, of 13 and 17 years, which are obviously prime numbers. Biologists tried to explain this phenomenon with some theories, among which we find the one stating that prime number were selected by evolution, since in this way the two broods would have had less chances to meet, avoiding to share resources.

We created an agent based evolutionary model in which the agents represent the cicadas; there are different species of agents, who differ for the length of their life cycle. In our experiments we used life cycles going from 1 to 20, since beyond wouldn't have been realistic, being *magicicada septendecim* the longest living insect in the world. In the proposed model we have a finite number of resources, and the agents must compete for them; when their time comes, the agents "come out" and must eat, before being able to reproduce themselves. Those who can't find food die, while the ones who can live; also predators are present in the model. This is another threat for the insects, and some of them are caught and eaten by predators; the one who survive can reproduce themselves and then die of a natural death. The children inherit the life cycle length from their parents; of course, if no cicada of a brood is alive, then that class is extinct and disappears from the simulation. Our model features a set of modifiable parameters, such as the reproduction rate, the number of predators, the maximum allowed life cycle and the probability to be alive after the period spent underground; this last parameter increases with the time, since in nature it's been proven that a longer life is a better option.

We presented two different sets of results from our model; in the first one the parameters are quite realistic, with a very high reproduction rate. We examined the quantities of cicadas at four different times: after 20, 1000, 5000 and 20000 years/tics. In our first run we have that the species which are still existent after 20000 years are the ones with a life cycle of 13, 17 and 19 years. This is a great result, since it mimics the real world; 19 years is not applicable in the real world since it's too long a life cycle for an insect, but anyway it's a prime number itself, proving that the basics of cicadas life cycles can be a biological prime number generator.

In the second experiment we wanted to concentrate on central values and see what happened; we then lowered the reproduction rate and the probability to be alive at the "wake up" time. The results were interesting again; the selected species were again two prime numbers, 11 and 17 and an even number which, of course, is prime for them, that's 14. Anyway the cicadas with a 14 years long life cycle showed a negative trend; they would probably disappear in the long run, living only the two prime numbers.

This model of evolutionary biology merges and validates with an agent based technique some different theories. We presented some robust results which partially confirm the "myth" of periodical cicadas being a biological prime number generator. In future works we'd like to increase the maximum life spam value, even if this is not biologically possible, to see if the prime numbers theory holds for larger numbers. Besides we'd like to implement hybridization among different species, which could be a strengthening mechanism for the mentioned "predator satiation" hypothesis. 2004 has been the latest year of "Brood X", in North America, during which there has been the major outbreak of the 17-year cicada (figure 9.

Fig. 9 Magicicada Septendecim

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