Genetic Algorithms in Resource Economic Models

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A way to model bounded rationality in resource exploitation?

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Abstract: The paper describes the application of Genetic Algorithms to a Resource Economics problem: the decision about the intensity of exploitation of a renewable resource. Genetic Algorithms, developed by HOLLAND (1975), are a model of biological evolution, that captures some important features of evolution in general: selection, recombination and arbitrary mistakes. They have therefor also been used already to model economic evolution and learning processes. The model will be based on two main assumptions. First, the agents using the resource are not informed about its reproduction dynamics. And second, although profits are their only concern, they are not able to calculate the optimal extraction rate that would maximize present value of all present and future benefits, like in neoclassical Resource Economics. This is caused by restrictions on the informational as well as the "intellectual" level, all referred to as "bounded rationality". The paper explains the model and its results. It then discusses problems of the application of a biologically motivated procedure to social evolution and makes some suggestions for a better adaptation of Genetic Algorithms for the purpose of economic modeling.

Keywords: Genetic Algorithms, Bounded Rationality, Resource Economics, Ecological Economics

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1 Introduction

Genetic Algorithms (GA), originally developed by John HOLLAND (1975) as a simple model of genetic evolution, have swiftly "evolved" to be used in lots of different areas, including some economic models as well.[1] This paper describes the application of GA to a Resource Economics problem: the decision about the intensity of exploitation of a renewable resource. The model will be based on two main assumptions. First, the agents using the resource are not informed about its reproduction dynamics. And second, although profits are their only concern, they are not able to calculate the optimal extraction rate that would maximize present value of all present and future benefits, like in neoclassical Resource Economics. This is caused by the lack of information referred to in the first assumption, as well as by other information shortages (future prices, demand, interest rate, etc.) and a limited "computational" or intellectual capacity, all referred to as *bounded rationality* by the literature of Evolutionary Economics (see e.g. CONSLIK 1996).

In traditional Resource Economics, only a small part of these restrictions to rational choice was taken into account. In fishery economics for example, there exist some models, which consider uncertainty by including a variance in the reproduction function of the fish. The probability distribution of the future fish stock given however, the fishermen in those models are still optimizing present value of all (expected) profits.[2] This paper sustains the opinion, that real economic agents are far less skillful than the ideal "homo oeconomicus", an assumption broadly discussed by Evolutionary Economics, but not yet taken up by Resource Economics. Less traditional Ecological Economics is talking about uncertainty, but most times, this just leads to political concepts like a "safe minimum standard" (CIRIACY-WANTRUP 1952) or the "critical natural capital" (PEARCE & ATKINSON 1993 or TURNER 1993). If bounded rationality is taken into account, this doesn't conduct to a new kind of models, but only to another form of political recommendations, like by FAUCHEUX & FROGER (1995) who took up SIMON's notion of a "procedural rationality" as a possibility for step-wise decision making in

[1] For an overview of different applications see GOLDBERG (1989: 126-129).

[2] For a brief description of the models of CHARLES (1983) and REED (1974) see FAUCHEUX & NOËL (1995).

uncertain situations. The model presented in this paper suggests to close this gap and introduces bounded rationality in a Resource Economics model. The agents in this model undergo a sort of learning process, in which their strategies are "evaluated" by the environment and changed by copying other agents strategies or strategy-elements.

After a very short introduction to Genetic Algorithms in the following section 2., part 3. is describing the model in detail (3.1-3.3) and explaining the results of the simulations (3.4). In these, different parameter settings and different relations of the catching potential to the reproduction ability of the resource have been tested. The interpretation of the model's results in section 4. reveals, that there are some interesting insights to be obtained. The GA generates time-series, which, compared with empirical time-series or intuition, look convincing. There are however some problems with the application of a procedure, originally designed as a model for biological evolution, to an economic process. These, as well as other question related to economic models including GA, will be discussed in the 5th section, which also makes some suggestions for modifications, intending to better adapt the GA as a description of economic processes.

2 Genetic Algorithms

A GA consists in a number of *strings* containing information about how to behave in their environment and some operators, changing the strings. After "behaving", the strings are evaluated by a *fitness function*, representing their environment, and the better adapted strings get higher scores. These in turn are important for the probability to be chosen by a *selection* operator, that determines which strings are allowed to reproduce. The chosen strings then undergo a procedure of *crossing-over* and *mutation*, and the so built "offspring" forms next periods generation that undergoes the same operations.

Because of their notable power to improve and find good solutions even in confusing or changing environments, the GA, initially developed as a *descriptive* tool, were often used as an *optimization procedure* for complex technical or logistic problems as well. Economic applications of GA are laying somewhere in-between those two interpretations. On one hand, the algorithm seems to be attractive as a procedure that is able to describe *bounded rational* behavior. In that case, especially in changing environments, such as e.g. the stock market, they do not necessarily reach equilibria (see e.g. ANDREONI & MILLER (1995) or DAWID (1997)). On the other hand however, there seems to prevail a strong desire to keep close to the neoclassical optimization idea and only get a better description of the *way* to equilibrium. Some of the models motivated by this idea, modify the procedure in order to enable it to reach an equilibrium, even in situations where the simple GA isn't apt to do so (see ARIFOVIC 1994).[3] We are

[3] LAWRENZ (1999) also uses the additional "election operator" developed by ARIFOVIC.

going to discuss this point in section 5. In the following model, GA are going to be used as a descriptive tool.

When using GA in an economic context, the operators of the algorithm are interpreted as steps of a learning process. A string is an idea or a market strategy of an agent. Selection and the related fitness function are the economic environment of the agents and the success they have. The designer of the model has to decide however, in what variable this success expresses itself: profits, market share, average profits of the last n periods or other. New ideas are then developed by recombining or copying successful old ones (crossing-over), including some mistakes or “unmotivated” experiments (mutation).

3 The model: A profit oriented fishery with GA generated catching potential

3.1 Assumptions

Differing from traditional Resource Economics, the basic assumption of the following model is, that the reproduction dynamics of the resource is unknown to its users. To make things less theoretic, let’s assume a population of the fantasy-fish “Spraty”. In a first time, the fishermen are extracting arbitrary amounts of “Spraties”, according to their catching potential. The only variable they can directly influence is their boat size. This size in turn determines their fixed and variable costs. Larger boats cause higher fixed costs but allow for a higher catching potential at lower variable costs per fish. Variable costs are of course rising with a decreasing amount of fish. So the optimal boat size changes with the size of the “Spraty”-population. The actual catches do not only depend on the catching potential of one fisherman alone but also on total catches of all. The more important total catches are in the first time-steps of one catching season, the faster variable costs are rising for everybody. At some point, it might not be profitable to go out fishing any more, even if the theoretical catching potential - that’s to say the boat - is still existing.

For comparison with traditional models it’s assumed, that the only concern of the fishermen is profit maximization or, more precisely, making as much profit as possible. Only, differing from those models, they don’t really know how to do that. They don’t know anything about the development of the fish-population except for how much fish they could get at what costs in the last period. So what they are able to attempt, is not the maximization of present value by filling in the blanks of some equation. They only know how much benefit other people made and can “decide” whether to keep their own strategy or to adopt elements of other peoples strategies. As we are going to see in the discussion of the model, this “decision” is in fact just a stylized one, because of the specific adaptation procedure, imposed by the way a GA works. Benefits are returns minus fixed and variable costs.[4]

The variable the GA is working on is boat sizes. This implies that the fishermen are looking at the profitability of other peoples strategies and less fit strategies are "dying out", whereas the fitter ones are copied or recombined. This is completed by a certain probability of making mistakes or arbitrarily including new elements.

3.2 Description of the equations

The reproduction dynamics of the "Spraties":

Like other fish in Resource Economics, "Spraties" are developing according to a logistic growth law (HAMPICKE 1992):

$$\dot{N} = \frac{s}{M} N (M - N) \tag{1}$$

with N as the current population size, M as carrying capacity and the growth parameter s.

For M = 800 and s = 1 we would get the following stock-depending offspring ($\dot{N}$):

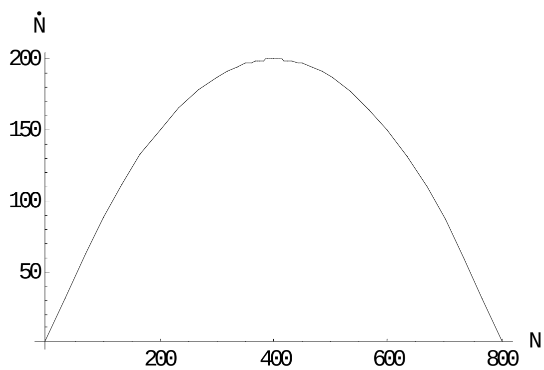

Figure 1: Stock-depending offspring

Catching potential:

Each string of 0 and 1 in the GA is encoding a certain boat size. A string has 10 positions of 1 and 0, that are decoded in boat sizes between 0 and 10. Each boat has a catching potential of 2 times the boat size:

$$cP = 2 \times b \tag{2}$$

Returns:

[4] Of course, one could easily implement other objectives than the traditional economic one, like e.g. an interest in a sustainable use of the resource and therefore a search for knowledge about the exact population dynamics. However in this model we want to have a look at the differences between the results of a traditional model and a GA under the same basic assumption.

The price of a “Spraty” is normalized to 1. Therefor the returns are given by the amount of fish caught.

Fixed costs:

The fixed costs are rising non-linear with the boat size. For the biggest boat they reach ¼ of the catching potential:

$$fK = \frac{b_{\max}}{2}\left(\frac{1}{b_{\max}} \times b\right)^2 \tag{3}$$

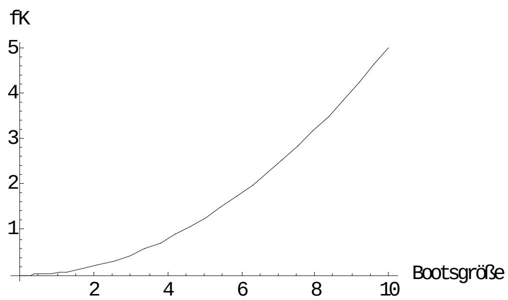

Figure 2: Fixed costs for different boat sizes

Variable costs:

The variable costs are decreasing with boat size and increasing with a decline of the fish-population. For the smallest boat and maximum stock they start with 0.5 to reach 1 at ½ of the maximum population. Therefor, for small boats, this is the point where fishing is definitely not profitable any more. But these costs are declining with larger boat sizes, so that - without considering fixed costs - large boats can still make benefits with a stock smaller than M/2. For the smallest boat variable costs are 10 times as high as for the biggest one. F stands for the number of fishermen.

$$vK = -\left(\left(\frac{M}{2}/N\right) - \frac{\frac{M}{2}/N}{F}\right)/(b_{\max} - 1) \times (b-1) + \frac{M}{2}/N \tag{4}$$

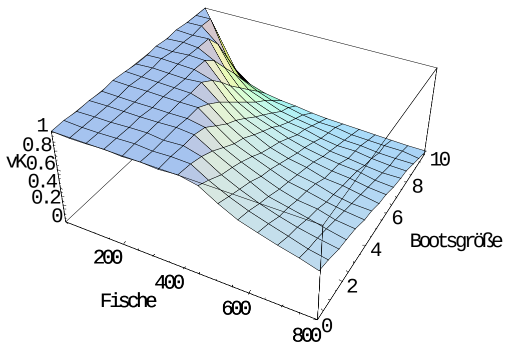

Figure 3: Stock dependent variable costs for different boat sizes[5]

[5] Fische = fish and Bootsgröße = boat size. The vertical axis was cut at the value of 1 (the price for one unit) to show the region which is profitable at most.

Actual catches:

The catching potential calculated above is only realized, if at least the variable costs are covered by the catch. However those are rising with a diminishing of the fish-population as we have just seen. We could just as well say that total costs have to be covered, which would be sensible in the long run, but for short term decisions, like the one whether or not to go out fishing with a boat you already have, only variable costs are important:

$$vK < 1 \tag{5}$$

Benefit:

If (5) holds, the catching potential is realized. The price for a “Spraty” is normalized to 1. So total catch (C) equals returns (R). The benefit (B) is:

$$B = R - vK \times C - fK \tag{6}$$

Reproduction:

The offspring is calculated using (1) after deduction of the amount of fish caught:

$$\dot{N} = \frac{s}{M}(N - C)(M - (N - C)) \tag{7}$$

3.3 The Genetic Algorithm

Selection:

The boat sizes are varied by a GA. After an arbitrary initialization the corresponding catches are realized and attributed their benefits. This is the orientation of the fishermen for the boat size of next year. The higher the benefit the more likely a string is chosen for reproduction, with F as the number of fishermen and S_p as the probability to be chosen:

$$S_{pi} \quad = \frac{B_i}{\sum B_i}, i = \{1 - F\} \tag{8}$$

Strings are chosen two at a time. The same string can be chosen several times, which is very likely if it’s an unusual good one, and the procedure is repeated until we have as much strings for the formation of the next generation as we had before in the old one.

Recombination:

With a certain crossing-over probability (c_p) a pair of strings is cut at an arbitrarily chosen location and the resulting ends are exchanged. FREEMAN (1994) set (c_p) 0.75. Here we’ll see simulations with:

$$c_p = \{0.4, \quad 0.75, \quad 0.9\} \tag{9}$$

Mutation:

Each position of the string can be changed from a 0 to a 1 or vice versa with a certain mutation probability (m_p), which can have different values. The original value chosen by FREEMAN (1994) is 0.001.

$$m_p = \{0.00001, \quad 0.001, \quad 0.008, \quad 0.02, \quad 0.05\} \tag{10}$$

After the generation of these new strings their catching potential is realized and evaluated, and then the strings are again modified by the GA.

The operators of the GA can be interpreted economically to form 3 types of learning behavior. The mutation rate stands for experiments with new ideas and for mistakes in own or copied strategies. Recombination is responsible for the other two types of learning. A high recombination rate expresses an interest in innovations which are realized by incorporating parts of other peoples strategies. On the other hand a low recombination rate stands for the more careful approach to imitate the whole strategy of someone else without taking the risk to make a bad match.

3.4 Results

The Simulations were run with all possible combinations of the mutation and crossing-over probabilities for four different cases:

1. Maximum offspring equals maximum catching potential (M = 800 and s = 1). In principal a sustainable use at MSY is possible.
2. Regeneration of the “Spraties” is reduced to s = 0.5. Maximum offspring is only ½ of the maximum catching potential now.
3. M = 800 and s = 1, but we have 20 fishermen instead of only 10. So again maximum offspring is only ½ of the maximum catching potential.
4. Changes of the boat size are only allowed every 2nd, 5th or 10th period.

1. Maximum catching potential = MSY:

If the maximum offspring is high enough to cover maximum catching potential the optimum boat size would be almost the biggest one possible (9.99). For an optimum stock of 414 benefits of 13.7 monetary units per fisherman could be realized (see Figure 4) - that’s a total of 137.

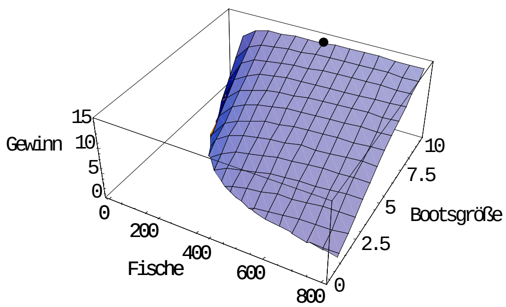

Figure 4: Profitable region and benefit maximum for MSY = cP_{max}[6]

In this very favorable case the fish population remains very high and stable in spite of the catches. For a low and medium rate of experiments (m = 0.00001 and 0.001) the stock converges with only a few fluctuations close to the optimum of 414 or slightly above.[7] For a high ratio of experiments (m = 0.008 - 0.05) the stock is fluctuating a lot more, but still the level stays quite high. In terms of the population of the fish a sustainable use is therefor always attained (see Figure 5 - 8).

Convergence of total benefits depends only on the mutation rate. The relation of innovation to imitation doesn't seem to be important. For a low and medium rate of experiments (m ≤ 0.001) benefits are always converging at a high level but not necessarily at the optimum. After a transient period of 10 to 20 time-steps there are almost no more fluctuations (see Figure 5 and 7). However this very inflexible fishery risks to converge far below the optimum that could be reached without problems from a sustainability point of view (see Figure 6).

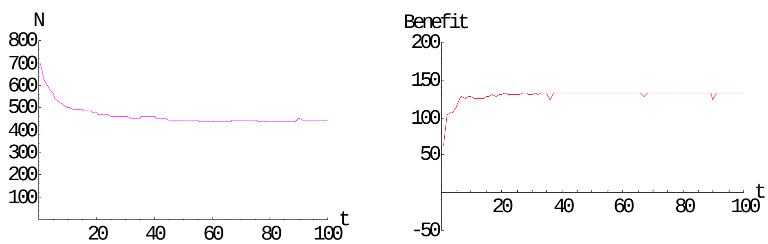

Figure 5: MSY = cP_{max} (c = 0.75, m = 0.001), 1. example

[6] Gewinn = benefit, Fische = fish and Bootsgröße = boat size.

[7] The Figures show a stock slightly above the optimum level (450 fishes). This is caused by the distribution of the boat sizes in the model. If we have boats close to the largest one possible a change in one of the back locations of the string doesn't change much at the fitness of the boat. So it happens very often that boats are slightly smaller than the optimum which causes lower catches and a higher stock.

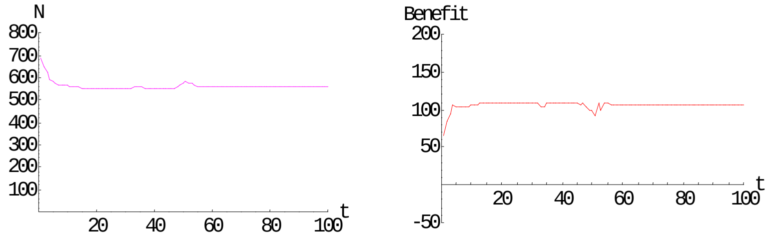

Figure 6: MSY = cP_{max} (c = 0.75, m = 0.001), 2. example

A tendency to convergence is still observable for medium rate of experimentation (m = 0.008), but it's blurred by constant fluctuations. However, in contrast to the less flexible fisheries, a benefit level close to the optimum is always attained, but it can take some time and undergo temporary Lock-Ins at intermediate levels (see Figure 7).

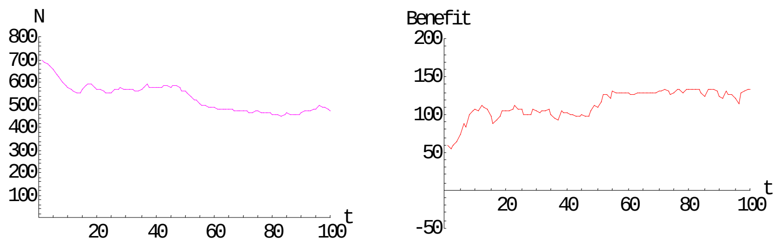

Figure 7: MSY = cP_{max} (c = 0.75, m = 0.008)

A further raise till 0.05 accentuates the amplitude of the short term fluctuations and initiates important drops and upraises of sometimes up to 50 monetary units. Average benefits fall to about 100 to 110, which still is relatively high (see Figure 8).

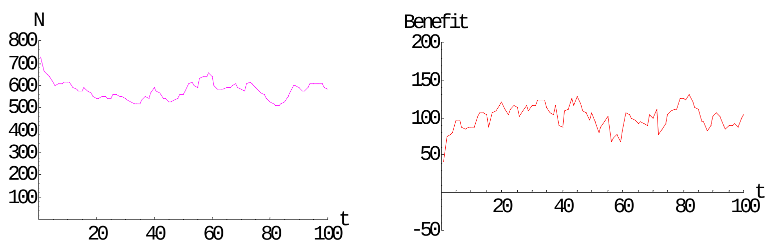

Figure 8: MSY = cPmax (c = 0.75, m = 0.05)

Summarizing we see, that in this model with a sufficiently high reproduction ability, "Spraties" are always used sustainable and profitable. Losses don't ever occur. However the fishermen aren't always able to learn the optimum strategy. When only experimenting a little, they always reach a high level but risk to settle down up to 20% below the optimum. The best results are realized with a slightly higher experimentation rate, which guaranties an approximation of the maximum benefit without however a real convergence.

Maximum catching potential = ½ MSY:

The second case is harder to learn for the fishermen. Therefor we can often observe larger fluctuations of the stock and benefits. Maximum offspring isn't high enough to cover the possible catching potential. The ideal boat would be of size 4.6. Benefits in the optimum would be 4.2 or 42 altogether. The fish-stock should be at 513, which is more than in the former case, but generates less offspring, because of the lower regeneration parameter.

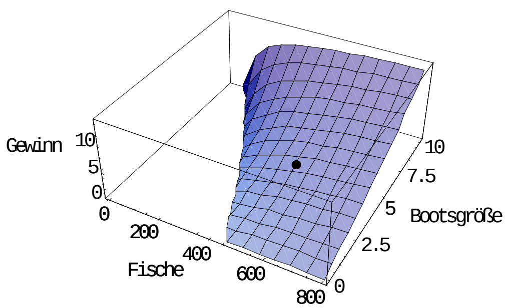

Figure 9: Profitable region and benefit maximum for MSY = $cP_{max}/2$[8]

Like in the former case, stability in those simulations is only depending on arbitrary changes of the strategies (mutations) and not on the relation of innovation to imitation. In all experiments with these parameters the supposed abundance of “Spraties” incite rising benefits up to 100 monetary units in the first 10 periods. This in turn causes “Spraties” to decline considerably almost to extinction and the fishery starts to make losses (see Figure 10 - 13). For a low and very low probability of experiments the fishermen are most times unable to change their strategies and work profitably again. However, if they manage to do so, a long-term sustainable use is possible (see Figure 10).

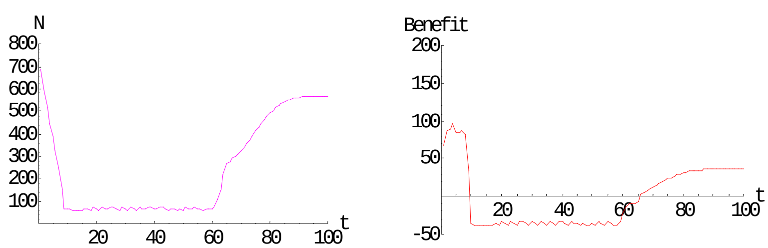

Figure 10: MSY = $cP_{max}/2$ (c = 0.4, m = 0.001)

If more experiments are made (m ≥ 0.008) stock and benefits are fluctuating considerably, but in contrast to the more stable cases they are able to rise again after a declining period. This leads to “exploitation cycles” which are reminding biological predator-prey-cycles - except for the losses of the fishery. The maybe most interesting phenomenon connected with those cycles might be the delayed feed-back. In a first time, it seems as if benefits could rise eternally. Higher costs caused by a decline of the fish-population are more than compensated by larger boats. But underlying this expansion, which can go on for more than 20 periods, is a sinking

[8] Gewinn = benefit, Fische = fish and Bootsgröße = boat size.

regeneration potential of the fish which can not be detected by benefits only, but finally leads to a sudden break down (see Figure 11).

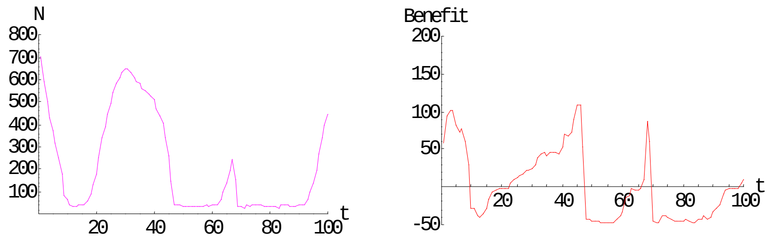

Figure 11: MSY = $cP_{max}/2$ (c = 0.9, m = 0.008)

If the rate of experimentation is still augmented the cycles get shorter. The stock of fish reaches a lower population level before declining, but on the other hand is also able to regenerate faster after break-downs, because the fishermen are more flexible. The time of rising benefits is reduced to 15 or 10 periods (see Figure 12 and 14).

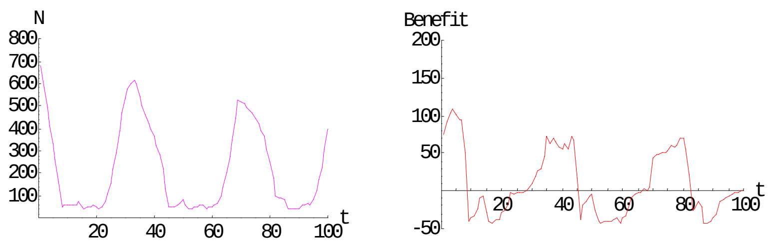

Figure 12: MSY = $cP_{max}/2$ (c = 0.75, m = 0.02)

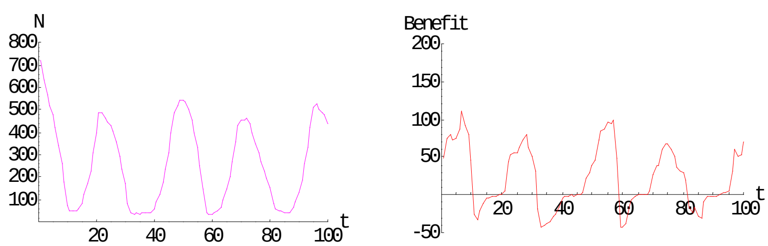

Figure 13: MSY = cPmax/2 (c = 0.75, m = 0.05)

20 Fishermen, MSY = $cP_{max}/2$:

The optimum boats size here is 4.6, the stock of fish after catches is 506. We have 20 fishermen instead of 10, so the individual maximum benefit of 4.9 is summed up to 98 altogether.

Especially for a medium rate of experiments the "Spraties" are often extinguished. The flexibility of the fishermen is sometimes high enough to discover a profitable strategy but not high enough to react as fast as necessary to losses (see Figure 14).

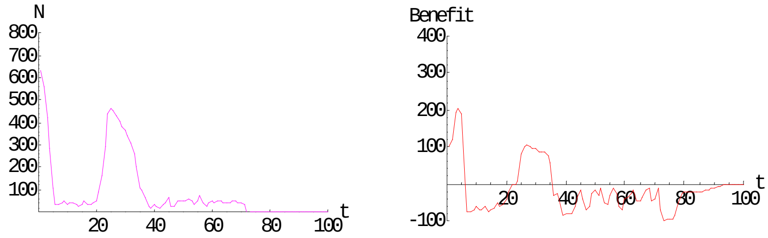

Figure 14: 20 Fischer, MSY = cPmax/2 (c = 0.75, m = 0.008)

When only experimenting a little, extinction isn't as prominent as before. However this is only due to the fact, that the fishery almost never manages to regenerate from losses after an over-exploitation in the first periods. Sometimes an exploitation at a low level of benefits and stock is possible (see Figure 15).

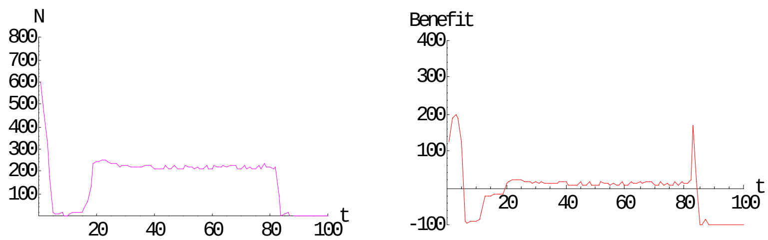

Figure 15: 20 Fischer, MSY = cPmax/2 (c = 0.75, m = 0.001)

Only for a high ratio of experiments we see exploitation cycles like in the former case but with a shorter succession (see Figure 12). Extinction however is still very probable because most times the stock is reduced dangerously close to 0. Therefor in 50% of the simulations the "Spraties" are dying out.

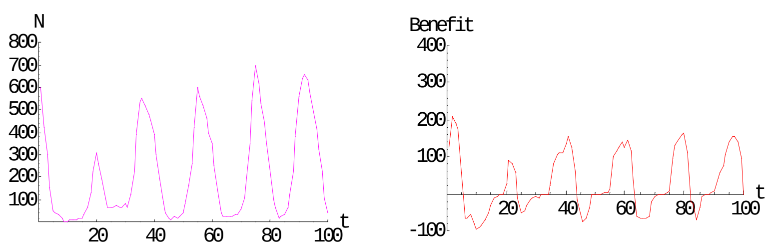

Figure 16: 20 Fischer, MSY = cPmax/2 (c = 0.75, m = 0.02)

Fixed boats sizes for 2, 5 or 10 periods:

The former models all allow for a change of the boat size in every period. Especially for large variations this doesn't seem very close to reality. It might be more realistic, to assume, that once an investment in a specific boat is made, the fishermen are bound for a certain time. Therefor we are going to investigate what influence on the results a restriction of new choices to every 2nd, 5th or 10th period has. We are not however taking into account, that new investments wouldn't take place all at the same time. The very pronounced stair-wise form of the curves is therefor due to the simplified assumptions.

If maximum offspring is high enough to satisfy the whole catching potential (MSY = cP_{max}), the fishery is almost always able to rise continuously to the optimum (see Figure 17 and 19). If boats sizes are only fixed for 2 periods there is no important deviation from the unrestricted model to be seen. It's not surprising, that the time till the maximum is reached is the longer the longer boat sizes are fixed, because learning only takes place every 2nd, 5th or 10th period. Therefor the development of a fishery which is bound for 10 periods is quite similar to the first 10 periods of the more flexible case.

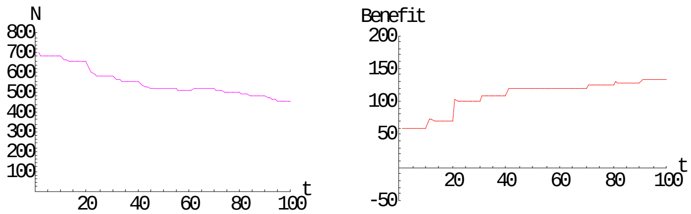

Figure 17: Boat sizes 10 periods fixed, MSY = cP_{max} (c = 0.75, m = 0.008)

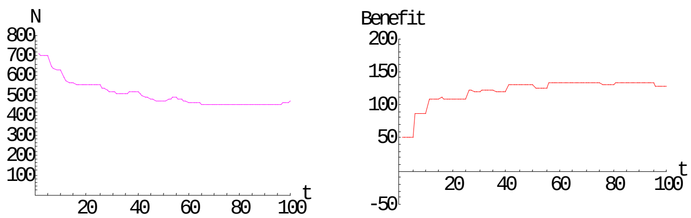

Figure 18: Boat sizes 5 periods fixed, MSY = cP_{max} (c = 0.75, m = 0.008)

If maximum offspring is only ½ of the maximum catching potential, the effect of the restriction is more important. In case of boats that are fixed for 10 periods, the fishery is always sliding down in the negative region. After a profitable start the fishermen are even augmenting their boat sizes when the first decision to change can be made after 10 periods. The "Spraties" are then highly overexploited between the 10 and 20 period and are barely able to regenerate afterwards. In a first time, the decline of the fish population is even accentuating the trend for large boat sizes, because, due to their lower variable costs, bigger boats are able to remain longer in the profitable region. When passing the line of losses, large boats make higher losses, because of their higher fixed costs, but (due to the prescribed inflexibility) some "bull-headed" are still keeping them. As soon as the fish population is slightly rising and variable costs are sinking enough to make catches profitable again, they are heading for the few fish available and reducing the population again, so that the fish has little if any chance to regenerate (see Figure 19).

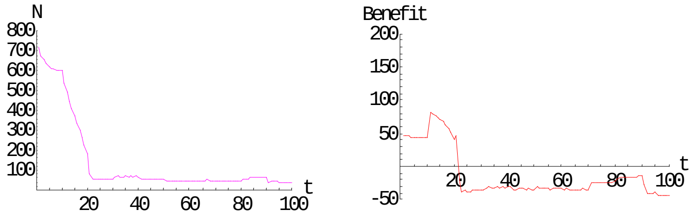

Figure 19: Boat sizes 10 periods fixed, MSY = cP_{max}/2 (c = 0.75, m = 0.008)

Fixing boat sizes for 2 or 5 periods in contrast stabilizes the development compared to the more flexible MSY = cP_{max}/2 case. This is partly caused by the above mentioned expansion of the scale. There may however also be another reason for this phenomenon. These short terms of inflexibility seem to be the appropriate ones to generate a balancing time-lag. In the following example, due to the retarded learning behavior, boat sizes are growing only moderately between periods 30 and 40, in spite of a strongly rising stock of fish. This causes the fishermen to be better prepared for the following reduction of the fish population. Their smaller boats cause lower fixed costs and the catches are stopped earlier, because of higher variable costs. So the fish-population has a chance to stabilize at a higher level (see Figure 20).

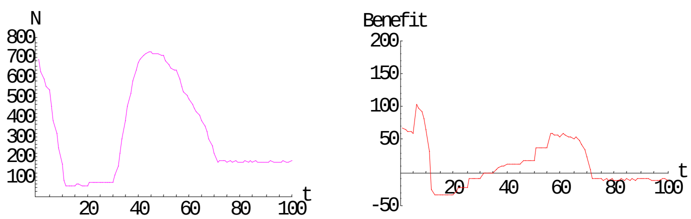

Figure 20: Boat sizes 5 periods fixed, MSY = cP_{max}/2 (c = 0.75, m = 0.008)

4 Discussion of the results

4.1 Main observations and parameter setting

The above simulations reveal some insights which might be surprising at first glance. The stability of profits and stock are only depending on the mutation rate of the algorithm. Crossing-over, whose probability was varied from 40% to 90% doesn't seem to influence the results at all. This observation is in stark contrast to the biological importance of crossing-over, where the mixing of successful strategies seems to be of much more importance than arbitrary mutations. However, when having a closer look at the model, these counterintuitive results become more clear.

In this simple model, the strategy of the fishermen consists in just one aspect, the variation of boat sizes. Costs are rising continuously, and therefor we only have one benefit maximum for each model. This in turn implies, that the closer a boat is to the optimal size the better it is. Except for special cases, where a medium boat size is optimal and the so far best boats are very small and very large ones, it doesn't make much difference, whether successful boats are mixed or copied as a whole. This considering we see that the model - like, by the way, other GA models as well[9] - lacks an important aspect of real world decisions. Usually strategies consist of more than just one variable, so that different agents can be successful for different reasons. Then a mix of those elements might be even more successful than the former strategies. The just described model doesn't make use of the potential of the GA to simulate such a process. For the simple strategies defined it makes almost no difference, whether they are mixed or just plain imitated. To really use the potential of the GA and to describe more realistic strategies, it would be interesting to have a look at models with more complex strategies, where a string is representing several aspects, each lying on specific parts of the string.

Concerning the effect of the mutation rate we saw, that low values of m = 0.00001 and m = 0.0001 generate a very or utterly stable behavior. A transient period of learning only takes place if the agents are heterogeneous at the beginning, but once this heterogeneity is leveled out, no more adaptation takes place. It seems obvious, that such a conservative behavior isn't very realistic for lots of market processes. It is however existing in some situations, such as the market dominance of products with rising economies of scale for the users.[10] Experiments with a medium mutation rate (m = 0.008) give a nice example for the fact, that even after long periods of stable fluctuations around a certain level, sudden changes can take place. This is an interesting observation, because those changes are generated endogenously out of the behavior of the agents. "Nonsense" or innovations can always occur, and if the exploited system is touchy enough, it might react strongly and alter the whole path of development. This innate characteristic of nonlinear dynamic systems is a fact often neglected by traditional economic theory, which attributes sudden deviations from a former equilibrium to external shocks. Raising the mutation rate still higher, creates very "nervous" systems and often blurs the effect of the transient phase as well as the possibility of abrupt changes. Therefor we should only do that, if the real world system to be modeled is very unstable indeed. Summing up, we see, that the definition of this parameter not only depends on the fundamental learning ability of the agents but also on the specific characteristics of the process to be pictured.

4.2 Comparison with traditional Resource Economics

Let's now have a look at differences, advantages and disadvantages of the GA model in comparison to traditional Resource Economics. Like in neoclassical models, the driving force of

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[9] In DAWID (1996b) the strings encode expected real return and are thus determining the supply of some good. ARIFOVIC (1994) also let the GA determine a production quantity for a cobweb model. In ANDREONI & MILLER (1995) or LAWRENZ (1999) the GA is working on two parameters of a bidding function in an auction, but these are not actually two parts of a strategy.

[10] The most prominent example seems to be the market dominance of the VHS video system, which appears not to have been the best one to be chosen at that time.

the fishermen's economic activity is profit maximization. The choice of next years boat is driven by last years benefit for different boat sizes. However, in contrast to neoclassical models, the GA fishermen are extremely shortsighted and uninformed. Instead of maximizing present value of all present and future benefits, they are just trying to do better than last year. They are doing so without any knowledge about the reproduction function of the fish, and they make mistakes or arbitrary experiments. In that they are almost the opposite of the omnipotent homo oeconomicus, which of course is intended, because the motivation to use GA is especially the fact that the assumption of completely informed, utterly rational and wholly independent individuals is a little doubtful. However the just modeled "blindfold" aren't very realistic either of course, even if some decisions, especially in common property cases, are made as if people didn't know anything about resource development. More precisely we should recognize, that they just don't care, because regeneration potential isn't something they could manage and use on their own account.

The effect of the short-sightedness is, that even for constellations which allow for an easily attainable profit maximum from a bioeconomic point of view, we can observe an adaptation phase of several periods, and optimization isn't guaranteed. Even a once reached maximum isn't kept exactly but suffers from constant fluctuations.

Simulations with a reproduction capacity which is not sufficient to allow the maximum possible catches deviate even more from the traditional models. Differing from those competing agents don't meet at the point where marginal costs equal marginal benefits and then remain there (HAMPICKE 1992). What we do see in contrast is a cyclic development with times during which exploitation is rising to far, because of a seemingly abundance of fish, followed by times of low profitability or losses, due to the overexploitation not early enough recognized. Extinction in these models isn't a sure event, depending on the cost-benefit-structure, like in neoclassical models, but only a probability. Part of these cycles are recurring sudden breakdowns of the fish-population. Such abrupt reductions of resource availability are a phenomenon often discussed in Ecological Economics, but despite this awareness there are only some predator-prey-models coupled with traditional economic use (Cobb-Douglas equations), that are able to show internal reasons for such events (e.g. CLARK 1990, STRÖBELE & WACKER 1991 or BECKENBACH 1994).

A further main difference between the above - as well as other - simulations including stochastic elements and analytical models is the fact that each simulation represents an individual history of the modeled system. Instead of one unique path of development we get a multitude of - most times - never quite identical tracks. If we want to predict the systems behavior - as economists and other scientists often are requesting - we can only give an indication about possible directions of the development and probabilities for certain kinds of behavior. This might be regarded as an inconvenience and is often used as an argument against such simulations. We should be aware however, that *if* these models are able to capture reality better than the analytical ones - which isn't sure yet -, we have to be careful about requesting analytical exactness at the cost of empirical significance.

5 Are Genetic Algorithms an adequate tool to model learning behavior in economic contexts?

Let's start this chapter with the provoking title of a working paper by CHATTOE & GILBERT (1998): "Just how (un)realistic are Evolutionary Algorithms as representations of social processes?" At first sight the results of the above simulations look promising. Given the sole intent of maximizing profits, the development of this artificial fishery seems to come closer to empirical data (see CLARK 1990: 322) than the unambiguous results of traditional analytical models, where the fish are always either exploited at a constant rate or extinguished (FAUCHEUX & NOËL 1995). We have to be careful however, when deciding whether this happens by mere chance or because the GA really captures the relevant aspects of economic development. As we have seen in Chapter 2, an interpretation of the operators of a GA in an economic sense is more or less straightforward. When having a closer look at the procedure, there are however important differences between the GA and human learning or strategy choice.

First of all, this originally biological model is restricted by the features of *biological reproduction*. Two individuals meet and "exchange" information that creates one or more (in the above model two) new individuals. It's obvious, that human information exchange doesn't necessarily take place *pair-wise*. It is however not obvious, to decide ad hoc what kind of information exchange would be more adequate. Some kinds of information are available to (almost) everybody interested, such as statistical data, the stock market development or TV news.[11] But there are for sure still lots of specific facts, like for example a detailed production strategy or the mixture of Coca Cola, only attainable through relationships between two or more people or trough industrial espionage. The problem therefor is, to decide what kind of information transmission seems the right one for the specific phenomenon to be modeled. For our fishermen for instance, it could be assumed, that other peoples boat sizes and profits are known to more than one competitor. But even more important seems to be the fact, that the influence of information exchange isn't very likely to be *mutual* most times. This biological transmission pattern isn't valid in social sciences, but it's easy to remedy.

A second difference between biological and human information transmission not to be neglected is related to the genotype/phenotype-distinction. In biology no individual is able to "guess" what genes are responsible for a visible physical appearance or behavior of another

[11] This kind of information availability is implicitly assumed by synergetic models in social sciences. Everybody knows what everybody else is doing - or more precisely, what percentage of the population is doing one thing or another (see WEIDLICH & BRAUN 1992 or WEISE 1993).

individual, but it doesn't need to find out, because the genetic information is exchanged directly. This might not be that easy in learning contexts. CHATTOE & GILBERT (1998: 17) are commenting quite cynically on this point. According to them, it would be more realistic to assume telepathy straight away, than to believe, that entrepreneurs are able to derive other people's strategies from their market results. There is of course some truth in that, but it might not be as bad as that. It's obvious, that just having a look at a firms benefit doesn't allow a reconstruction of its whole production program. But of course that's not what competitors are doing. A firm's success only accounts for a first orientation of its competitors. The following imitation of it's strategy requires a closer look at possible reasons for this success. It's true, that a GA doesn't model the process of information gathering behind the superficial selection operator, but we can assume, that it is taking place in the background. BECKENBACH (1998) took this point into account by associating the crossing-over activity with search costs. Another interesting idea would be to suppose that recombination or imitation includes a lot more mistakes (mutations) than in biological reproduction, due to the somewhat obscure picture of others' "genotype".

The third and maybe most important limitation, is the explicit and sometimes even implicit lack of several *cognitive aspects* human learning exhibits:

- memory
- internal selection
- motivation and satisfaction level

GA are an aimless searching procedure. There is no conscious intention and no reflection in its search, and there is no awareness of past experiences. All these missing points indicate, that GA "learning" is in fact a very stupid and unconscious one, which isn't surprising, because biological evolution - the blueprint for this procedure - isn't actually learning in a human sense. When discussing the lack of the above cognitive aspects in GA, we should try to distinguish between permitted simplifications each model has to make, and real shortcomings of an unaltered application of GA to human strategy development.

The most undisputed point may be the lack of *memory* in GA. It's true, that a memory is only advantageous if similar situation are recurring and that "In non-stationary environments, agents are always bound to try to understand future behaviours of other agents or future events that had never occurred in the past " (DOSI & EGIDI 1991: 151). But we still can assume, that at least some patterns are reappearing and that experience plays an important role in human decisions. Therefor it should be tested, if the results of a modified GA, including a memory, would differ much from the simple one.

This point is closely related to the one of *internal selection*. If the agents would have a memory, they could compare new strategies with old ones or have a look, whether those "new" strategies haven't already been tried and didn't work. Even without a memory, after generating a new strategy, an agent could have a break and think about its potential, given last periods information, instead of just executing it blindly. This amounts to internal selection, not yet included in GA. In some economic applications of GA this is solved by the creation of an *election operator*. New strategies are only executed, if they would have been more successful under last periods circumstances (see ARIFOVIC 1992 or LAWRENZ 1999). This seems to be a worthwhile suggestion. It might however be a too strict avoidance of fantasy and error making.[12]

Some authors don't seem to agree with the application of GA to human decision making at all, because they think, that external selection by the environment doesn't play an important role in those processes (see WITT 1997 and BRENNER 1998). "Fitness in social evolution is rather subjectively determined" (Brenner 1998: 19). Inasmuch as it's certainly true, that subjective fitness criteria play an important role in human decisions, it's nevertheless doubtful, that external restrictions are less significant. A possibility to model this kind of internal selection, was proposed by CHATTOE & GILBERT (1998) or BECKENBACH (1998). They suggest to represent each agent by its own *internal GA*. The strings then are different ideas of the same person and are evaluated by an internal (subjective) fitness function. The fitter they are, the more likely they are chosen for external execution. The ideas chosen for execution could then be transmitted to an external GA, like in the simple model, to take the *competition between agents* into account.[13]

The least convincing point, concerning missing cognitive elements in GA, seems to be the sometimes criticized lack of a *motivation* for change or of *satisfysing behavior* (see BRENNER 1998). A motivation to improve is implicitly existent, because less well performing strings disappear and fitter ones reproduce or ameliorate. Even if all strings are identical, the occurrence of mutations can be interpreted as a still prevailing motivation to look for better solutions. The larger the differences between the strings are, the faster adaptation takes place. This could easily be interpreted as a kind of satisfaction level, which in some mathematical models is defined as the ambition to be at least as good as the average (see e.g. EBELING, SCHARNHOR'ST & KARMESHU 1997). Naturally the desire for change slows down, if there are no more others to be seen performing better. We could include an explicit condition, stating that mutations or crossing-over are only taking place, if some specific success level isn't satisfied, but it's doubtful, whether that would be a useful modification. First of all, my suggestion would be, that it wouldn't make a big difference for the results - except maybe for a slight slow down. Second, this would imply, that only less successful agents would try to improve, whereas it seems more plausible, that - analogous to biologic evolution - the more successful

[12] Steps from one slope to a another (steeper) one are only allowed, if they occur at once, without passing by an intermediate valley.

[13] A similar tool was developed by HOLLAND with his *Classifier System* (see HOLLAND et al. 1987).

individuals are more likely to have the (financial and intellectual) potential for further ameliorations.

Besides the just discussed problems because of the biological origin of the GA there are some technical questions as well: *encoding* and *parameter setting*. The results of a simulation with GA can strongly depend on the parameter setting (LANE 1993a). Differing from analytical models, simulations require an *explicit* definition of each parameter. We can't derive general results, such as the Resource Economics insight that marginal regeneration ability has to equal the discount rate, *without* having to know the absolute figures of either (ENDRES & QUERNER 1993). The only way to test the effect of different values is to vary the parameters, which is sort of time consuming and can be difficult or again time consuming to evaluate. Concerning the learning procedure itself, one possibility to define the relevant parameters is to calibrate the model to fit experimental data, like ARTHUR (1993) did, using the results of a simple psychological learning experiment. Of course, this still doesn't prove, that the simulation captures the important aspects of real learning behavior. Models that are able to reproduce empirical data might make the modeling more plausible (LANE 1993a), but we have to be aware, that some time series are very simple to reproduce by lots of different mathematical procedures, which doesn't mean, they were originally generated by this same procedure.

Last but not least we have to think about the plausibility of the chosen *en- or decoding* of the string.[14] Holland's GA uses binary strings which are decoded to the corresponding decimal numbers. This signifies, that the farther to the left a 1 or 0 is situated in the string, the more important it is for the final value. A mutation of the leftmost location in the string causes a doubling or cutting in half of the former value. Mutations of different locations however all have the same probability. It might be worth to think about either a subsequently rising probability of mutations from the left to the right end of the string or some sort of Grey-code, equalizing the contributions of different locations to the final value.[15]

6 Summary

Including uncertainty and bounded rationality is not yet common in Resource or Ecological Economics. However the dynamics of resource development, especially under economic exploitation, can't always be supposed to be well-known. This paper presented a model that allows to model resource exploitation under bounded rationality. The agents don't know the

[14] There are, of course further critical points, which can't all be mentioned here. For further criticism see e.g. CHATTOE & GILBERT (1989), BECKENBACH (19998), WITT (1987) or BRENNER (1998).

[15] The arbitrariness of a specific encoding procedure is sustained by the fact, that other, similar procedures, like KOZA's *Genetic Programming* or RECHENBERG's *Evolutionary Strategies*, use other ways of encoding (see KOZA 1992 or RECHENBERG 1973).

reproduction dynamics of the resource and they are not able to derive the optimal exploitation rate to maximize the present value of all returns.

This is realized by using a Genetic Algorithm that generates the catching potential of economic agents exploiting the fantasy-fish „Spraty“. The success of different catching potentials or strategies is measured by the profit of the agents and this depends on resource availability and the catching potential of other agents. Strategy modifications are effected by the operators of the GA: selection with a higher probability for the more successful strategies and generation of new strategies by mixing the selected old ones and including some arbitrary changes.

The simulations were run for different parameter settings and different relations of the reproduction capacity of the resource to the catching potential. The simulations showed, that whether or not the fishermen learned to use „Spraty“ sustainable solely depends on the rate of arbitrary experiments (mutations). It wasn’t important whether they just plain imitated other agents’ strategies or invented new ones by mixing successful old ideas. This result - surprising at first sight - is caused by the very simple strategies, consisting in just one decision variable. Real decisions can be supposed to be much more complex. For a very low rate of experiments the simulations show a convergence that appears too stable for most social systems. More realistic looking time series are to be obtained for higher rates of experiments between 0.8 and 5%.

Compared with traditional Resource Economics models the simulations show some interesting differences. In cases with an abundance of the resource, the optimal exploitation can always be learned. This is consistent with analytical results. The learning might however take some time and some intermediate steps, which is a more plausible development than an instantaneous optimization. More important differences can be observed if we include actual resource scarcity. Whereas analytical models always issue at a conclusive solution, such as the use at a level where costs equal prices or like extinction, the simulations exhibit a cyclic behavior. After overexploitation the fishery brakes down, which leaves room for the fish to regenerate. These augmenting stocks however are than overexploited again. The pattern is recurring but never quite identical and extinction is the more probable the closer the cycles reach downwards. Compared with real time-series, including fishery data as well, this pattern seems to be more convincing than the unambiguous analytical results.

The simulations indicate that the use of GA in economic models might yield some interesting insights. A critical look at the application of GA to economic learning or development however, reveals that lots of aspects of human learning, such as memory, motivation or internal (pre-)selection of ideas are not included in this very simple and biologically motivated procedure. It has not yet been thoroughly discussed whether a modification of the algorithm is necessary or not. In its final section, the paper therefor made some suggestions for a better adaptation of GA for the purposes of economic modeling. Altogether Resource Economic models taking bounded rationality and uncertainty into account, by using GA or a further developed similar procedure, are a promising direction of economic research.

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