Applying Parallel Genetic Algorithms to Economic Problems: The Case of Agricultural Land Markets

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Abstract. This paper elaborates the use of distributed Genetic Algorithms (DGA) to study an artificial land rental market. The study is based on a spatial comparative-static model in which a number of spatially ordered agents (farms) compete in an auction for renting land. Each agent's behavior is determined by a genetic algorithm that is applied to an agent specific population of genomes representing particular bidding strategies. Agents interact directly through a migration mechanism that allows to spread renting strategies across the population of agents as well as indirectly over the rental market. Two market constellations are considered and different simulations with a variety of parameter constellations (migration rate, placement of farms, etc.) are run: First, a situation of limited market access is defined. A series of simulation experiments shows that for this scenario the DGA generates results that fit comparative static equilibrium conditions like allocative efficiency and zero-profits. Second, in a limited market access scenario, only under very special conditions the DGA generates results that comply with oligopolistic behavior. The results of the two scenarios are analyzed and discussed as to the influence of the DGA procedure itself and a possible economic and game theoretic interpretation.

Keywords: Genetic Algorithms, Game Theory, Land Market

1. INTRODUCTION

Since their introduction by Holland in 1975 Genetic Algorithms (GA) have been used in a number of disciplines. Based on the application of the evolutionary concepts of selection, crossover and mutation on a population of behavioral strategies, their primary use has been in the field of optimization. Besides this, GA have also become a means for modeling and representing particular types of economic problems. One reason for GA being an attractive tool for economic research has to do with the assumption of a normative behavioral foundation of individual action. In economics this is a very common assumption, and it makes models analytically tractable. The downside of this procedure is that it demands other strong assumptions like homogeneity, unbounded rationality and convexity. However, in reality one will hardly find economic agents perfectly behaving like economic models want them to behave. Therefore, instead of a normative behavioral foundation, it appears to be a promising alternative among others to derive individual behavior from artificial intelligence methods, of which GA are one. Because they always involve a number of strategies competing against each other GA-based economic models can be interpreted particularly well in a game theoretic context.

2. APPLICATIONS OF GENETIC ALGORITHMS IN ECONOMICS

To motivate the kind of GA we apply in this paper, it is worth while looking at previous applications of GA to economic problems. Up to now, there have been quite a number of publications in this area (e.g. Marks 1992, Birchenhall 1995, Miller 1996, Axelrod 1997, Curzon Price 1997). In the majority of the papers GA are applied to well known standard economic models, such as cobweb-type models, the prisoner's dilemma, or industrial organization problems. One such example is the paper by Arifovic (1994) in which she applies a GA to a simple cobweb model. In game theoretic terms the cobweb-model can be interpreted as a symmetric game with Nash equilibria in pure strategies. The application of a GA to this problem is straight forward since the type of GA specified for this problem corresponds pretty much to standard GA specifications like the ones that can be found in GA textbooks (cf. Goldberg 1989, Mitchell 1996).

Dawid/Kopel (1998) present another application of GA to models of the cobweb-type. Their kind of cobweb-model also describes a symmetric game. But, unlike in the Arifovic model, the equilibrium is a Nash equilibrium in mixed strategies, i.e. some agents produce while others do not. As Dawid/Kopel show, for their model a simple application of the standard type of GA, as done by Arifovic, does not lead to a convergence to the mixed strategy equilibrium, but to a non-equilibrium situation. This indicates that it is necessary to adjust the GA-setup according to the specific problem in order to obtain a convergence towards a theoretically plausible results.

In reality, the majority of market situations are not as simple as economic models would like to propose. This is especially the case for individual actors in an economy, who display heterogeneous behavior, individual characteristics and goals. In terms of game theory this means that it is mostly asymmetric games that we can observe in reality. An example for such an asymmetric game could be an agricultural land auction market. Because agricultural production takes place in space, both the land plots and agents on the land rental market, i.e. the farms, are usually heterogeneous per se.

Balmann (1998) applies a GA to a model of such a land market in which a number of agents compete for renting the land from a central auctioneer. In his model in each iteration every farm agent follows only one bidding strategy. The GA procedure is applied to the whole population of farms and consequently alters the bidding strategies of the farms. However, strictly speaking, the application of just one GA procedure to the population of farms does not appear appropriate in the case of heterogeneous conditions. Firstly, to develop individual strategies for heterogeneous farms it would make more sense if farms would be able to evolve strategies which are adjusted to the their specific characteristics. Then, the effect of local interactions would be taken into account. This cannot be accomplished with just one single GA. And secondly, for a single GA, mixed strategies can only occur on the level of the population with the single farms playing pure strategies. But it would be desirable to include the possibility of each farm playing a mixed strategy, too. This is important in the context of local neighborhoods and space in general, as mentioned before.

This paper takes up these shortcomings and proposes a GA-based modeling approach to heterogeneous land markets. The complexity of the model goes beyond the analytically and theoretically well understood, but often simplistic models like the cobweb-model. In the following, first GA are introduced. Afterwards, the spatial and dynamic land allocation model to which the GA is applied is briefly sketched. Following this, three simulation scenarios and the respective simulation results are presented, discussed, and conclusions are drawn.

3. AN INTRODUCTION TO GENETIC ALGORITHMS

GA have been developed in analogy to the concepts of biological evolution and even the terminology is quite similar. Even though there is no 'standard GA' but many variations of GA, there are some basic elements common to all GA (cf. Holland 1975, Goldberg 1989, Forrest 1993, Mitchell 1996). The first task of an application of GA is to specify a way of representing each possible solution or strategy as a string of genes that is located on a chromosome. According to Figure 1 this can e.g. be achieved by transferring numbers into binary bits, i.e. zeroes or ones, that represent the genes. A complete set of genetic information is called a genome. A particular set of genes in a genome defines a genotype. The application of the genotype to a particular problem then gives the phenotype.

encoded solution (genotype)		decoded solution (phenotype)
…|1|0|0|1|0|1|1|1|…	←	rent offer: 906 DM/ha
…|1|0|1|0|0|0|0|1|…	←	rent offer: 966 DM/ha
…|1|0|0|0|0|0|1|0|…	←	rent offer: 780 DM/ha

Figure 1: Example of genotype - phenotype relations for rental strategies on a land market

The second task is to define a population of N genomes to which the genetic operators, i.e. selection, crossover and mutation, can be applied. Considering a population of solutions or strategies allows for a kind of parallel processing. The population size usually ranges between 10 to 50 genomes.

The basic GA-setup is very simple. In effect, in each generation GA process a population of genomes, and successively replaces one such population by another by means of genetic operators. The number of generations depends on the problem to be solved. It can range from some 50 to a couple of thousand. Most often a GA passes through the following steps.

Initialization at the Startup
In most GA applications the first generation of genomes is initialized with random values.

Determination of Fitness
Before the GA operators are applied, the effectiveness of the genomes in one population is evaluated by means of a fitness function. This function assigns a score to each genome in the current population according to its capability to solve the problem at hand. The better the solution solves the problem, the higher the fitness value. For the applications of GA to economic problems or to games, the fitness value is derived from the strategy's profitability or payoff.

Selection and Replication
Selection determines the genetic material that will be reproduced in the next generation. The fitter the genome (i.e. the more adapted it is to the problem) the more likely it is to be selected for reproduction. The most well known selection scheme, among others, is probably fitness-proportionate roulette wheel selection: Each genome is assigned a slice of the wheel, the size of the slice being proportional to the genome’s fitness. The next generation’s genome population is determined by spinning the wheel for each genome and replacing it by the genome at the slice where the marker stops. However, it is also possible not to spin the wheel for all members of the population but only for genomes not meeting a certain criterion

like a minimum required fitness value or those genomes that randomly 'die'.

Crossover
Crossover is a variety generating feature of GA, where pairs of solutions (parents) mate to produce offspring. Each offspring draws some of its genetic material from one parent and some from the other. Again, there exist many different forms in which this operator is applied to the population of genomes. Figure 2 shows the simplest case of a 1-point-crossover, where the coded strings of two parent genomes are split at a randomly chosen locus and the sub-strings before and after the locus are exchanged between the two parent genomes resulting in two offspring of the same string length.

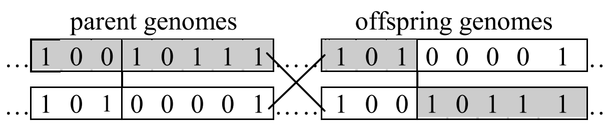

Figure 2: Example of a 1-point-crossover after the 3rd bit position

Mutation
Mutation also implements new genetic varieties into the population of genomes. Furthermore, mutation serves as a reminder or insurance operator because it is able to recover genetic material into the population which was lost in previous generations. This insures the population against an early and permanent fixation on a particular genotype. Mutation works in a way that the mutation operator flips each bit of a genome in each generation with a fixed probability that is generally very low (e.g. 1:1000 per bit).

The simple GA, as it is described above, imitates the basic ideas of natural evolution on a very abstract level. It forms the basis for the theoretical analysis of GA. But, for real problem solving its power is limited in several respects. Simple GA ignore many useful ideas of biological evolution, like a multiplicity of chromosomes per genome, diploid chromosomes, and sexes. The encoding, the chosen fitness function and the implementation of the operators may not be the most effective ones. Therefore GA models often need to be extended to take account of the more complex reality (Mitchell 1996).

Since GA parameters usually interact non-linearly they cannot be optimized one at a time. According to Mitchell it is unlikely that any general principles of parameter settings can be formulated a priori considering the wide variety and complexity of problems. Choosing the probabilities for the different operators, of the fitness function, the coding rules, etc. is very much a trial and error process.

4. THE LAND ALLOCATION MODEL[1]

The land allocation model to which the GA is applied assumes a comparative static spatial rental market for arable land. The model interface in Figure 3 shows an agricultural region that is divided into different plots of land of equal quality. It is assumed that each plot represents an area of 100 ha with a border length of 1 km. To avoid border effects for the region, the region is assumed to have the shape of a torus (i.e. the surface of a 'doughnut'). At the outset of the model a number of agents is randomly allocated to some plots in the region.[2] The position of each agent is fixed on this plot. In an iterative auction the agents compete for renting the land. If an agent receives

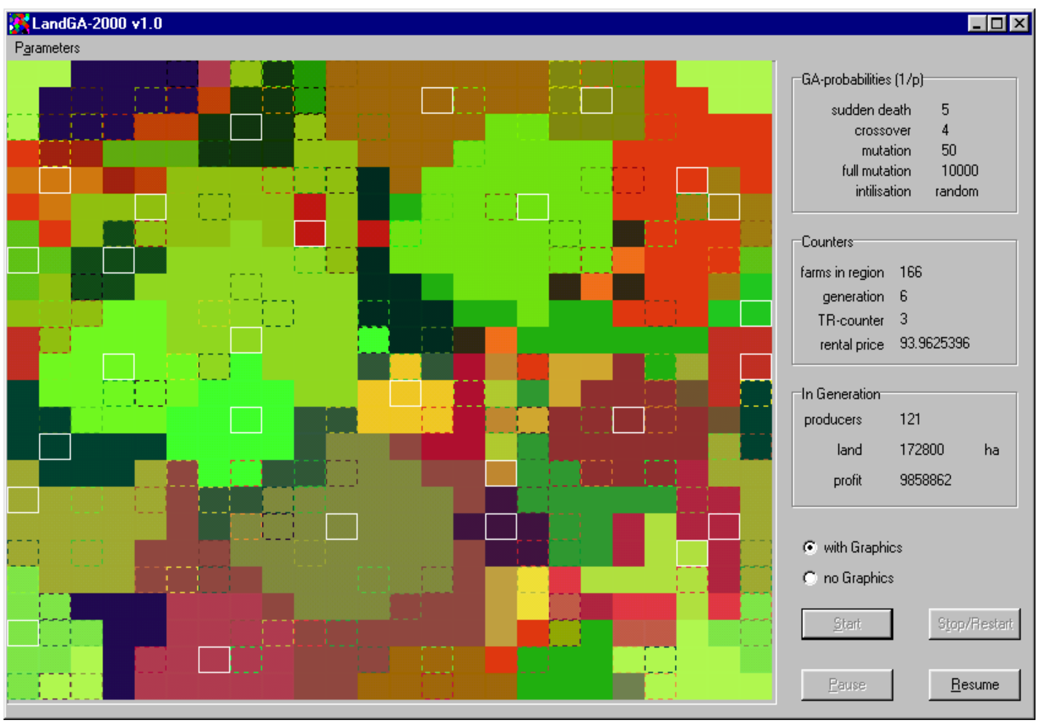

Figure 3: The model interface[1]

[1]) The program can be downloaded from "http://www.agrar.hu-berlin.de/wisola/fg/abl/ALFONS/GA/ga_ref.exe".
[2]) We interpret agents as potential farms because agents may choose not to take part in the land auction. And if they take part, whether the agent gets land or not depends on its neighbors' strategies, too.

land and engages in agricultural production, the location can be interpreted as a farmstead.

In Figure 3 the agents' locations are represented by boxes. If an agent rents land the particular plot is surrounded by a solid line, the line is dashed if the agent does not get any plots. Each color represents the plots rented by a particular agent (including the plot on which the agent is located).

Different from the simple GA described in section 3 and the studies by Arifovic (1994), Axelrod (1997), Curzon Price (1997), Balmann (1998), etc. in which each agent was represented by a single genome and the GA was applied to the whole population of agents, in this study a multiple-population approach is followed (cf. Cantú-Paz 1997). That is, each agent is associated with a separate population of 10 or more genomes - each of which represents a different renting strategy - and the GA procedure is applied separately to every population (Figure 4).

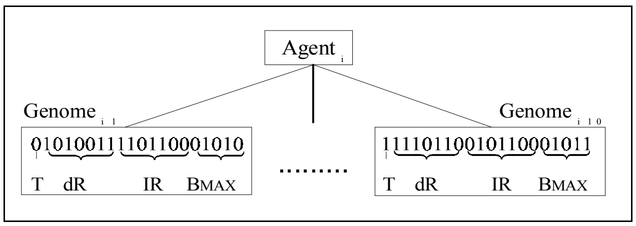

Figure 4: An agent's genome population

The application of individual GA should allow the agents to develop individual strategies that are adjusted to the individual location and neighborhood. Moreover, there are game theoretic implications. If an equilibrium of the model requires heterogeneous strategies, then a single GA would obtain this only by a heterogeneous genome population, as mentioned in section 2. In terms of game theory a heterogeneous population would have to be interpreted as a mixed strategy. A multiplicity of GA, however, allows the genome populations of the agents to be homogenous. This means that an equilibrium could also be reached with asymmetric pure strategies.

1. initialize the model
2. intial generation n = 1
   a) testing round t = 0
      i) initialize farm agents
      ii) do land allocation
      iii) determine fitness
      iv) repeat i) through iii) until t = number of testing rounds
   b) do genome migration
   c) GA procedure: selection, crossover, mutation
3. increment n by 1 (new generation) and iterate (go to step 2)

Figure 5: Flow chart of the model

4.1 The Model Structure

Figure 5 presents the order of events. At the outset of the simulation each agent is allocated randomly on a plot and random values are assigned to an agent's 10 genomes. In this particular GA model one generation consists of 12 iterations, the so-called 'testing rounds'. By dividing a generation into testing rounds it is insured that each genome's performance in the market can be tested at least once with a probability that is considered sufficient.[3] If a genome is not drawn in one generation it is assigned the average fitness of the agent's genomes. After this, the GA operates on the genome population of each agent.

Every testing round the model passes through three steps:

Step 1: Initialization of Agents
At the beginning of a testing round a genome n is drawn from each agent's genome population to determine this agent's strategy in the land auction in this particular testing round. The strategy is given by four strategy parameters: the participation in the land market (T_i),[4] the initial rent offer (IR_i), a rent differentiation coefficient (dR_i), and the maximum desired area (B_{MAXi}). For use in a GA these strategy parameters are transferred into binary code and aligned to a single bit string with the length of 48 bit.[5] Every string can be interpreted as one of the agent's genomes.
The rental price P_i agent i bids is determined by

$$P_i = \begin{cases} IR_i - dR_i \cdot B_i - TC_i(\cdot) & \text{for } T_i = 1 \text{ and } B_i < B_{\max,i} \\ \text{no bid} & \text{for } T_i = 0 \text{ or } B_i \geq B_{\max,i} \end{cases} \quad (1)$$

where $TC_i(\cdot)$ represents transportation costs to the next available plot depending on distance, acreage, and the marginal transportation costs '*tc*', while B_i is the amount of land that agent i already has rented in the testing round's auction.

Step 2: Land Auction and Allocation of Land to Agents
According to (1) every agent makes a bid for the closest free plot in its neighborhood. The agent with the highest bid receives the desired plot for a price equal to the bid. Thereafter, this agent calculates a new bid for the next

[3]) This extension of the simple GA is necessary, because several genomes per agent cannot be tested simultaneously.
[4]) The participation gene is a kind of switching gene, by which the strategy of an agent abruptly changes. The effect is that the GA can find Nash equilibria in mixed or asymmetric pure strategies more easily (Dawid/Kopel 1998) because the recombination of Nash-equilibrium strategies leads to equilibrium strategies, again.
[5]) Instead of binary code, the so called 'gray code' was used (cf. Nissen 1994). The advantage of gray code is that similar strategies have a similar code, which is not the case for binary code.

desired plot. The same applies to those agents who were also interested in the plot which was allocated last, but whose bid was not accepted and the bids are compared again. This process is repeated either until all plots are allocated or until there is no further positive bid.

Step 3: Determination of Profit and Fitness
After the auction in testing round t (t = 1,...,12) agent i disposes over a certain amount of land $B_{REAL\,i,t}$, which serves as the variable in the agent's economic rent function irrespective of transportation costs $X_{i,t} = g(B_{REAL\,i,t})$. The economic rent function is based on a study by Peter (1993) who applied an engineering approach to compute the economic rent function for arable farms under favored conditions which may be found in several regions in Germany. Figure 6 shows that for this setting the optimal farm size is about 2000 ha.

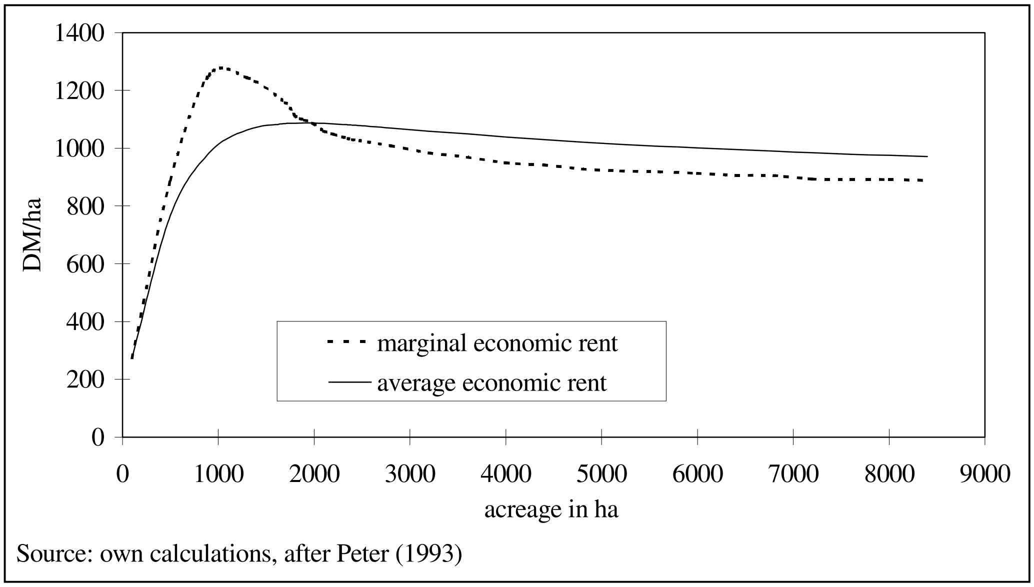

Figure 6: Marginal and average economic rent per ha depending on acreage

Agent i's individual economic rent function $W_{i,t} = h(B_{REAL\,i,t})$ is derived by subtracting the transportation costs which depend on the agent's total acreage and the location of the various plots from $X_{i,t}$. Thus, the difference between the individual economic rent and the total rent expenditure equals the agent's profit $\Pi_{i,t}$. The profit, again is an argument in the fitness function $F_{n,i,t} = f(\Pi_{i,t})$ of the selected genome n, which in return influences the probability of selection and replication in the agent's GA procedure.

4.2 The Genetic Algorithm in the Model

The GA is executed after 12 testing rounds and leads to a new generation of genomes. Prior to the GA procedure there is a migration of individual genomes between agents to allow for an imitation of relatively successful agents' strategies by other agents. Migration is implemented in a way such that with a fixed probability one genome from each agent's genome population is replaced by a copy of a genome from another, relatively more successful agent.

For our GA procedure we made the following assumptions:

Initialization: The genomes and the locations of the agents are determined stochastically.

Determination of Fitness: The fitness function for agent i's genome n in testing round t is specified in (2)

$$F_{i,n,t} = \left(\max\left(0; K + \frac{1}{A_n} \sum_{k=1}^{A_n} \Pi_{n,k} \right) \right)^{\beta}, \qquad (2)$$

where A_n is the number of testing rounds that genome n was tested since it acquired its genotype and $\Pi_{n,k}$ is the profit of test k. K has a value of 50000 and can be interpreted as a kind of initial capital endowment for each genome; β takes a value of either 0.95, 1, or 1.05. The parameters K and β have to be understood as scaling factors that affect the intensity of selection. The fitness function and the locations of the agents remain the same for all generations. Thus, each agent's population meets similar external conditions during the simulation. It is only the competitive situation between the agents that changes due to the strategies modified by the GA-operators.

Selection: In this model, selection is restricted to certain conditions. It is assumed that the selection operator only works on genomes with a fitness of zero and on genomes that 'die' with a probability of 1:5. The replacement happens as described in section 3.

Crossover: Each genome is paired with another genome with a probability of 1:4. The mating genomes are chosen randomly and they are paired in a 1-point-crossover with the two offspring genomes replacing the parent genomes.

Mutation: The mutation operator is integrated into the model such that at least one bit is inverted in each genome with a probability of 1:50.

5 SIMULATION

In the following, the proposed GA procedure is applied to the land auction model. We define and simulate three different market scenarios. Each of the scenarios depicts a characteristic market situation. Scenario 1 describes a very competitive situation in which many agents can freely access the land market. Scenario 2 depicts a large region with as many agents as there are needed for an efficient production structure. In this situation the market is 'on the verge' to an oligopolistic market structure. And finally, in Scenario 3 a market on which oligopolistic behavior is very likely to appear is simulated.

A detailed game theoretic interpretation of the market constellation and the strategic options of the farm agents is presented for the first scenario. As mentioned before each agent has an individual population of strategies. The fittest strategy in one such population is only the fittest relative to the other agents' behavior. Hence, the success of each agent's strategy depends on the strategies of the other agents.

5.1 Scenario 1: Unlimited Market Access

5.1.1 Some Ex Ante Equilibrium Considerations

The region considered in Scenario 1 has a size of 57600 ha and farms are located randomly on every 3rd plot, transportation costs amount to 20 DM per ha and km distance.

To begin with, it is worth wile to take a closer look at the comparative static equilibrium conditions for this particular competitive scenario. According to (1) an agent can follow two pure strategies: rent land (A), do not rent land (B). Now one can imagine three possible behavioral setups: All agents follow either A or B, or they follow a mix of strategies with a certain probability.

If all agents followed strategy A with equal bids the average farm size would be 300 ha. According to Figure 6 this is significantly below the optimal farm size and yields only an average economic land rent of about 600 DM/ha if transportation costs of 20 DM per ha and km are assumed. A farm operating near the optimum of about 2000 ha would yield up to 1087 DM/ha. Hence this situation is unstable: On the one hand, if the overall rent level is higher than 600 DM/ha farms would make losses, and agents not participating in the auction would be more successful because they wouldn't make any losses. On the other hand if rents are lower or equal 600 DM/ha, farms bidding marginally higher would be relatively more successful and receive significantly more land which allows them to exploit economies of scale. If all farms followed strategy B, and would not produce, the solution would also be unstable. Because then one or more agents that start bidding at low levels could make significant profits. Hence, a heterogeneous behavior of agents, with some producers and some non-producers, is a necessary condition for an efficient organization of regional production.

In Scenario 1 this efficiency condition is satisfied if about 30 of the about 200 agents distributed equally over the region produce at a size of about 2000 ha, whilst the rest does not rent any land. However, this situation can only be an equilibrium if producers and non-producers are equally successful. Otherwise there would be an incentive to move to the more successful group. Since non-producers make no profit by definition, in equilibrium producers should hence make no profit as well, i.e. the average rental price for land should equal the average economic rent.

In game theoretic terms – this was already briefly mentioned in section 4 - the situation just described is a game with an asymmetric Nash equilibrium in pure strategies (30 of 200 potential agents rent land at prices near the optimum, while 170 rent no land). But, because we allow for mixed strategies on the farm level, one may also expect a symmetric mixed strategy Nash equilibrium. Then each farm plays the pure strategy A with a probability of 30/200 and strategy B with a probability of 170/200. The mixed strategy equilibrium requires the agents' genome populations to be heterogeneous, i.e. to consist of different strategies. This equilibrium, however, is less efficient then the one in pure strategies.[6]

5.1.2 Scenario 1: Simulation Results

Figure 7 shows the development of economic rents, rental prices and profits for a simulation over 4000 generations. The values in each generation are averages over all testing rounds and farms in the generation. For generation 2000 to 4000 the average economic rent is 1059 DM/ha which is 97.5% of the maximum value of 1087 DM/ha. Consequently, the farms operate at sizes that are close to the

[6]) For a further discussion of game theoretic implications see Balmann/Happe (2000).

optimum with regard to their productivity.[7] The average acreage is 1970 ha, which is also very close to the optimum. Even though farm sizes fluctuate between 1700 and 2200 ha, economic rents which are close to the maximum are yielded. Rental prices and economic rents are almost congruent. For generations 2000 to 4000, on average, there are slight losses of about 4 DM/ha, which is less than 0.5 % of the economic rent. Compared to a similar simulation in Balmann (1998) (average economic rent of 1048 DM/ha which is about 96.5% of the optimal value, average acreage of 1651 ha) one can observe that the results have been improved with the use of a parallel GA.

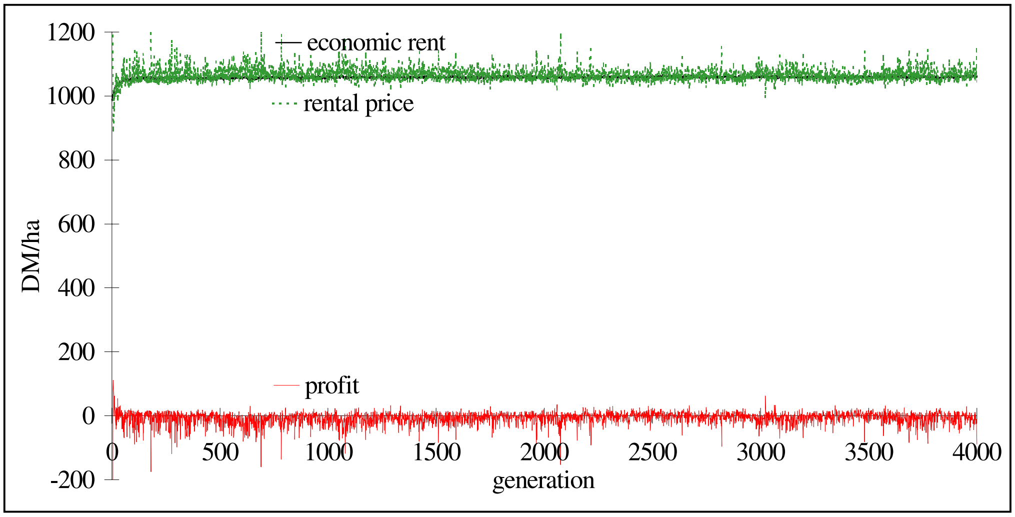

Figure 7: Economic rents, rental prices, and profits
(203 agents, 57600 ha, transportation costs 20 DM per ha and km, β = 0.95

The average losses of 4 DM/ha are mainly caused by unfavorable mutations, i.e. strategies which are associated with bids higher than the maximum economic rent. Altogether, these results lead to the conclusion that under the considered market conditions the co-evolving, GA-based agents are able to identify states which are quite near to the economic optimum and equilibrium. The most interesting aspect of this result is that it is not the individual agents who develop effective strategies. Rather, it is the fact that the collective of agents identifies this state in a self-organizing way without an external control. This has to be seen as an emergent property of the system (cf. Axelrod 1997, 4).

5.2. Scenario 2: Limited Market Access, Large Region

The previous simulation led to plausible results for the case of unlimited market access. We now look at what happens for the case of limited market access in a large region. We have introduced limited market access by significantly reducing the number of farm agents to a number such that all agents could theoretically produce at an optimal farm size an in cases. The GA parameters are chosen as described in section 3.2, though with a higher mutation rate. Because the access to the market is limited one could expect the farms to show oligopolistic behavior. This hypothesis would have to be rejected if it could be shown that the rental prices are equal to the marginal productivity in which case the profits would have to be interpreted as

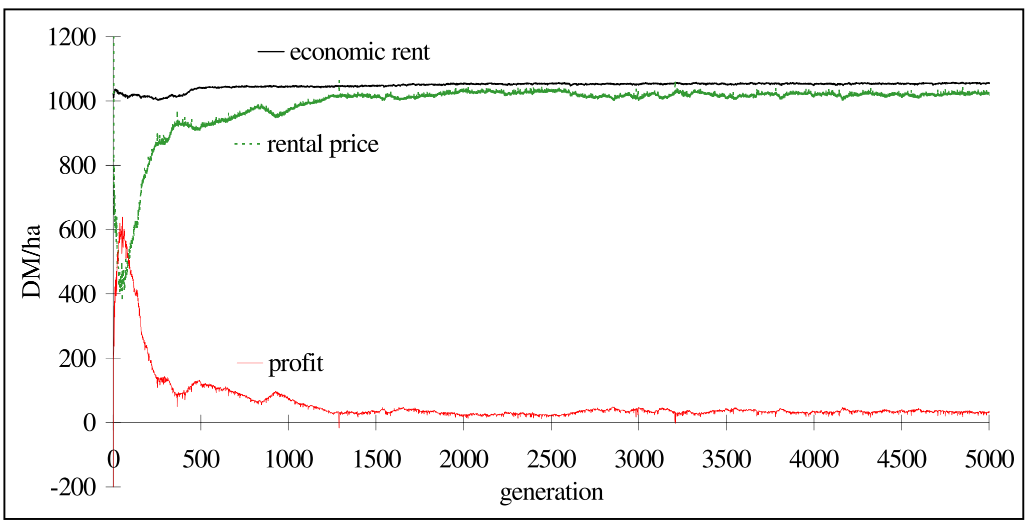

Figure 8: Economic rents, rental prices, and profits
(43 agents, 90000 ha, transportation costs 20 DM per ha and km, β = 0.95)

[7]) It is noticeable, how quickly the comparative static equilibrium is reached. In an additional simulation with all initial values set to zero it could be shown that this is not due to the initial random values assigned to the genomes at the outset of the simulation (cf. Balmann 1998).

Table 1: Theoretical and realized profits depending on transportation costs (TC) in DM per ha and km, data in ha or DM per ha)

				simulation results generations 3000 to 5000				*calculated figures [a]*
No.	*TC*	*region size (ha)*	*β*	*average acreage*	*economic rent*	*rental price*	*profit Π/B*	*W/B-∂W/∂B for B = 2200 ha*
1	0	90000	0.95	2288	1117	1104	13	14
2	20	90000	0.95	2267	1054	1020	34	36
3		90000	0.95	2956[b]	1030[b]	961[b]	69[b]	76[f]
4	60	90000	0.95	2240	950	888	62	79
5	120	90000	0.95	2143	806	662	144	144
6	200	90000	0.95	1927	667	482	185	231
7	20	6400	0.95	3168[c]	1052[c]	551[c]	501[c]	76[f]
8		12100	0.95	3000[d]	1062[d]	544[d]	517[d]	76[f]
9		12100	0.95	2999[e]	1047[e]	543[e]	504[e]	76[f]

[a] Calculated differences between marginal and average economic rent (W) according to Figure 6 for an acreage of 2200 ha and an ideal location of plots.
[b] Periods 2000 - 25000. [c] Periods 7000 - 13000. [d] Periods 3000 - 10000. [e] Periods 2000 - 25000. [f] *B*=3000 ha.

resulting from farms producing with decreasing returns to scale.

The simulation results are shown in Figure 8. For generations 3000 through 5000 the average farm size is 2267 ha. The average economic rent of 1054 DM/ha contrasts an average rental price of 1020 DM/ha such that the average profit is 34 DM/ha. Such profits are rather small to support the hypothesis of large farms showing oligopolistic behavior.

To get deeper insights into this, a series of simulations was conducted for different transportation costs, farm sizes, and region sizes. Table 1 shows for the simulations no. 1 through 6 that profits increase particularly with transportation costs. Unfortunately, due to the heterogeneous spatial distribution of farms the marginal productivity can hardly be computed. Alternatively, the average profits Π/B can be compared to the difference between average and marginal economic rent (W/B-dW/dB).[8] The most right column of Table 1 shows this difference for a farm size B of 2200 ha. Its calculation is based on the productivity relation presented in Figure 6 and an ideal location of the plot relative to the farmstead.

According to Table 1, for simulations No. 1 through 6, the realized profits are lower or equal to the difference between the marginal and average economic rent. It can be concluded that these profits do not result from oligopolistic behavior, but from polypolistic behavior of farms with decreasing returns to scale.

Even though the considered limitation of market access implies some distributive effects, its allocative effects are rather small. Considering marginal transportation costs of 20 DM/ha and km, allocative effects are only apparent in the fact that the economic rent of simulation no. 2 is 1054 DM/ha compared to 1059 DM/ha to 1080 DM/ha in the scenarios with unlimited market access. This is a loss of less than 2.5 %. On the one hand, this decrease in efficiency results from a less flexible spatial distribution of agents. On the other hand the lower efficiency is due to the fact that not all agents produce in each generation. Otherwise the average acreage per agent would only be 2093 ha instead of 2267 ha. Reasons for this can be found in mutations. According to Balmann (1998) it is possible that strategies arise which exploit the weaknesses of the GA, i.e. its fluctuations. For instance, farms following very low bidding strategies may potentially receive significant amounts of land, and make enormous profits. In other periods the same strategies may not be successful at all and other farms rent more land.

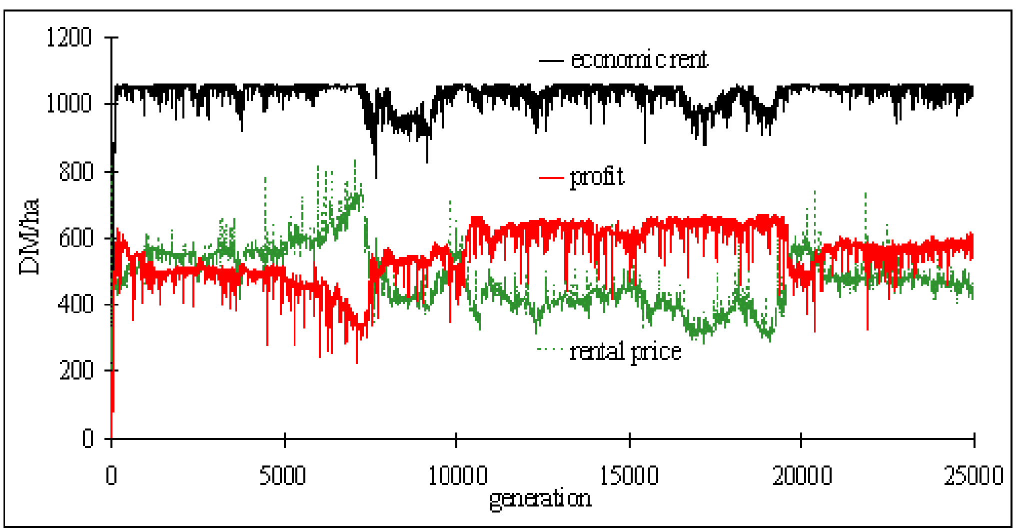

Figure 9: Economic rents, rental prices, and profits
(4 agents, 12100 ha, transportation costs 20 DM per ha and km)

[8]) Proof: If the rental price r is equal to the marginal economic rent of land $\partial W/\partial B$, i.e. $r = \partial W/\partial B$, and the profit Π is equal the difference of the total economic rent and the rental expenditures, i.e. $\Pi = W - rB$, then $\Pi/B = W/B - \partial W/\partial B$.

5.3. Scenario 3: Limited Market Access, Small Region

Because there was no evidence for oligopolistic behavior in the previous scenario, we now look at limited market access in a small region of 12100 ha, in which only four farms compete for renting the land.[9] Figure 9 shows the results. As one can easily see, significant profits do emerge. Moreover, as simulations no.7 through 9 in Table 1 show, average profits amount to around 500 DM/ha. Compared to the calculated difference between the average and marginal economic rent of 76 DM/ha based on Figure 6 for a farm size of 3000 ha, this is clear evidence for oligopolistic rather than price-taking behavior of the farms in a small region. Hence, the results of Table 1 have to be interpreted in a way that oligopolistic behavior does not occur in sufficiently large agricultural regions, even though farms are large, market access is limited, and - due to substantial transportation costs - a rather small number of farms competes for a particular plot. Oligopolies only emerge in small closed regions, like islands. Obviously, the fact that each farm's neighbors compete with different other farms causes at least an indirect competition among all farms. In other words, overlapping neighborhoods lead to overlapping areas of competition. This seems to prevent local oligopolies. Probably, there is a strong parallel between this spatial effect and overlapping generations in dynamic models (cf. Arifovic 1996).

6. FINAL REMARKS

This paper analyzed the application of distributed or parallel GA to a spatial agent-based model. Three market scenarios were defined and simulated. The results were discussed with regard to their compliance with some comparative static equilibrium considerations.

For the case of Scenario 1 (unlimited market access) the simulation results comply with comparative static equilibrium conditions. If one looks at the limited market access in Scenario 2 and the question of emerging oligopolistic behavior, the results are not as clear. But as Scenario 3 shows, oligopolistic behavior does only emerge under very restrictive conditions, such as a small number of farms in a small region. Even if in Scenario 2 transportation costs are very high such that large farms compete locally with only a few farms, oligopolistic behavior did not emerge in sufficiently large regions, despite the fact that farms did make some profits in this case. But, since these profits do not exceed the difference between average and marginal costs, even under these conditions farms act as price takers.

This and other conclusions, however, assume the model to be valid. Despite our claim to present an application of GA to a complex economic problem which takes account of agents' heterogeneity and other stylized characteristics of the agricultural sector, there are still many shortcomings which need to be mentioned, too.

The land allocation was based on an auction, while in reality, rental contracts usually result from bilateral negotiations. Moreover, the assumption of a comparative static production function neglects significant dynamical aspects. In fact, there are a number of frictions in agricultural product and factor markets (quotas, sunk costs) that stabilize existing structures even if they are not in equilibrium. Such frictions can explain severe differences in rental prices, too (cf. Balmann 1999). Consequently, the land market model should be dynamic, too. But this would require the GA to be applied to the problem for several hundred if not a couple of thousand generations per time step (period). If computing time increases multiplicatively with the number of periods, a dynamical model will quickly become intractable.[10]

Furthermore - as the simulations show - there are some more general problems related to GA. Since GA are still a rather young field of study and therefore not entirely analytically explored, there is a particular danger to generate artifacts. Due to the general difficulties to validate complex models, it is often difficult to attribute certain results to characteristics of the GA, to the specification of the model, or to the research question. Helpful for a better understanding of the behavior of GA is evolutionary game theory (cf. Dawid 1998). Existing theoretical studies concentrate rather on topics that deal with the technicalities of GA rather than on the practical problems with applications of GA to economical questions. Moreover, a multiplicity of interacting GA is very complex in itself. Its exact behavior is very difficult to study and understand since it is determined by a large number of parameters whose impact on the quality of the results is not well understood, yet (Cantú-Paz 1997, 1999). Therefore, if GA are to be applied to complex, analytically intractable problems, model development and analysis resemble much more a (time-consuming) trial and error process than a systematic procedure. Hence, the success of their applications depends on experience and reason as well as on opportunities to generate similar results by other means.

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[9]) It has to be mentioned that rental prices and profits in this case are not as stable as in the simulations presented before. This is because the strategies' fitness is very sensitive to the other farms behavior. Hence, in the case of a few farms only, mutations have a particularly strong impact on the results.

[10]) Just for the purpose of illustration: The computing time for the presented static simulations ranged up to almost a week on a fast PC for run each. Thus, a dynamic simulation might take months or would need exceptionally fast computers.

The evolution in a GA-based model should also not be confused with economic evolution. Even though the evolution of a GA can be understood as a kind of learning process (Arifovic 1994) GA learning is substantially different from the patterns of human and economic learning (cf. Chattoe, Dawid 1996, 1998). One should also be careful with transferring evolutionary ideas too naively. Terms like 'survival of the fittest' are misleading. Chattoe (1998) stresses that it is neither in nature nor in economies it is exclusively the fittest who survive. Rather, a firm's strategy has to be considered as viable if it is appropriately adapted, relative to other firms' behavior and success.

Last but not least, the agents' rationality in GA models is not only limited by the abilities of the GA itself, but also by the model concept. For instance in the presented model, the price differentiation of the individual agents only allowed for a linear variation of bids. Since the progression of the economic rent function is non-linear, the bidding function can only be optimized approximately by the GA. Otherwise, a more flexible decoding function would have to be defined.

A brief outlook at the end: The application of GA to the study of social processes is still at the beginning. Although GA will hardly replace conventional analytical approaches, they may serve as an alternative to conventional approaches in order to gain new insights into problems. GA can also contribute to a general reflection on conventional models in the light of new methods in the field of multi-agent systems. It is also possible to further develop normative models with the help of GA in order to use less restrictive assumptions. In the end, the scope of future applications of GA depends on the resourcefulness of potential users.

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