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Exploring the Agent Vocabulary
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Emergence and Evolution in System Dynamics

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Abstract:

Agent-based simulation is an approach increasingly used to describe and explain social phenomena; the areas of application are similar to system dynamics. Whereas system dynamics more or less ignores the agent-based approach, scholars from the agent-based community argue for the superiority of their approach. This paper analyzes in more detail two of those arguments: the impossibility claim concerning the ability of system dynamics models to explain emergent phenomena as well as their flaw as to not consider individual diversity.

Key Words: System Dynamics, Agent-Based Simulation, Emergence, Evolution, Heterogeneity

The Agent-Based Paradigm and its View of System Dynamics

Agent-based simulation is a simulation methodology increasingly used to describe and explain social phenomena (Sawyer 2003). It is a key assumption of the approach that those phenomena result from local interactions of agents one level below the phenomenon; global system control does not exist (Jennings et al. 1998). From a modeling perspective, the macro system behavior is generated by the behavior of individual entities, called agents, on a micro level (Schillo et al. 2000); thereby the agent becomes the basic building block of a model (Jennings and Wooldridge 1998). The concept of agency, however, is not at all well-defined (Rocha 1999). The agent-based literature identifies several different catalogues of requirements for an entity to possess agency; two prominent examples are autonomy and goal-directed behavior (Schieritz and Milling 2003).

Applications of the agent-based simulation approach are widespread. A very famous example and also one of the first models is Schellings (1971) checkerboard simulation of racial segregation. Other applications can be found in the analysis of traffic flow (Resnick 1994, Nagel and Schreckenberg 1992), of the behavior of social insects like bees (Dornhaus 1998) or ants (Bonabeau et al. 1999, Klügl 2001), of supply chain management problems (Parunak 1998) and many more.

Despite of the variety of applications the agent-based paradigm can be considered a relatively new approach for simulating systems in the social sciences; it is far from being an established research methodology (Sawyer 2003) what might be one of the reasons why researchers from the agent-based community put a strong emphasis on demarcating their paradigm from others. The struggle of a new paradigm to become established requires a critical mass of scientific manpower that is most easily found in young researchers who can (or even have to) choose between alternative paradigms (Kuhn 1962). As most of the time a knock-down argument for showing the superiority of an approach does not exist „ a major goal of contributions … is to convince the reader or listener, in a way that may well go beyond austere scientific argument and include rhetorics and other means“ (Balzer et al. 2001, paragraph 1.4). What Balzer et al. found for the 'battle' between Game Theory and Simulation is to some degree also true for system dynamics and agent-based simulation, with the difference that only one side 'fights': system dynamics seems to more or less ignore its 'opponent'. So, what is it ‚they' say about ‚us'? – Two examples:

> "ABM [agent-based modeling] is most appropriate for domains characterized by a high degree of localization and distribution and dominated by discrete decisions. EBM [equation-based modeling, where system dynamics belongs to] is most naturally applied to systems that can be modeled centrally, and in which the dynamics are dominated by physical laws rather than information processing." (Parunak et al. 1998, p. 15)

> "Economics models of utility functions assume the rational actor of economic theory; however, economists have long realized that such an actor is not very realistic, but the mathematical methods of EBM make it difficult to relax this assumption. MAS, by drawing on cognitive science, allow the representation of actors that use a wide range of decision strategies, both rational and nonrational." (Sawyer 2003, p. 331).

The aim of this paper is to analyze in more detail two arguments the agent-based literature gives for the superiority of agent-based simulation to system dynamics: the inability of system dynamics models to explain emergent phenomena and their flaw as to not consider individual diversity. The paper is therefore divided in two sections: Section one challenges the impossibility claim concerning emergent phenomena. Moreover, the theories of emergentism that underlie the agent-based and the system dynamics approach are identified. In section two the effects of evolution on population dynamics are analyzed comparing a system dynamics model of two species competing for resources with its agent-based counterpart. The consideration of individual diversity leads to high complexity and limited applicability of the system dynamics model, however it is shown that a highly aggregated more 'system dynamics like' model of an evolutionary process displays similar results.

Part I: System Dynamics and Emergence – a Contradiction?

Emergence is a central concept for agent-based simulation (Sawyer, 2001). Many pragmatic articles aim at the analysis of emergent phenomena (Resnick 1994, Bonabeau et al. 1999). Other, methodological papers, often use the concept of emergence to underpin the superiority of agent-based modeling for the analysis of social systems: emergence, they argue explicitly or implicitly, as a central problem of the social sciences (Sawyer 2001), is best investigated with agent-based approaches. More concrete, arguments go as follows:

> "The classical modelling of real systems by the use of differential or difference equations often are "top down" approaches: the system is looked at as a whole – from "above" – and its behavior, i.e. its dynamics is defined via the changing of its states, described by the according system's equations. … Yet more suited for the tradition of social theory is another approach that is called – in contrast to top-down procedures – as "bottom up". Basis for the analysis is not the system's behavior as a whole but the level of single elements and their interactions with other elements; the behavior of the whole system, i.e. its dynamics is with bottom up procedures an "emergent" result of the strictly locally defined interactions between single elements." (Klüver et al. 2003, paragraph 2.3f)

> "Many traditional approaches to simulation … have taken as their starting point macro-level abstractions … These models embody many high level assumptions and are therefore commonly tautological – encapsulating the basis of what they are intended to explain. Conversely, agent based approaches avoided intermediate explanations, attempting to reproduce macro-behavior by changing micro-agent details and interactions." (Goldspink 2002, paragraph 3.3)

Comparing different social science simulation techniques Gilbert and Troitzsch (1999, p. 12f) explicitly deny the system dynamics approach the ability to be of any help in the analysis of emergent phenomena when they write:

> "In Table 1.1, the 'number of levels' refers to whether the techniques can model not just one level (the individual or the society), but the interaction between levels. A technique capable of modelling two or more levels is required to investigate emergent phenomena."

	Number of Levels	Communication between agents	Complexity of agents	Number of agents
System Dynamics	***1***	No	Low	1
…	…	…	…	…

Figure 1: Gilbert and Troitzsch's inferiority proof

So, what is this "thing" that a system dynamics model is not capable of investigating? This is a question the agent-based community itself is at variance about. Although a lot of authors agree in the fact that agent-based modeling is most suited for the analysis of emergent phenomena there is a lot of discord in the question what such a phenomenon is. Gilbert and Troitzsch (1999 p. 10) assume emergence to be an objective characteristic of a system when they identify an emergent phenomenon as one that "requires new categories to describe it which are not required to describe the behavior of the underlying components." Bar-Yam (1997 p. 10) on the contrary takes a purely subjective view when he calls definitions that consider emergent behavior as "behavior not captured by the behavior of the parts" as a "serious misunderstanding". Instead he states that emergent behavior "is not readily understood from the behavior of the parts". An additional, very different component is added by Holland (1998) who states that emergent phenomena have to be regular, meaning recognizable and recurring.

Despite a great discord concerning the phenomenon most authors agree that a system has to possess at least the following two requirements in order to be capable of showing emergent behavior: nonlinearity and a hierarchy of system levels. A linear system can be fully understood by decomposing it and analyzing the individual parts.[1] This does not hold for nonlinear systems: in nonlinear systems the interaction between components results in distortions that do not allow for system decomposition (Goldspink 2002).

The second necessary requirement, the existence of at least two modeling levels, is a result of the assumption that emergence is a macro phenomenon that results from interactions of components on a lower level (Sawyer 2001). As made clear by the above citations of Goldspink (2002) and Gilbert and Troitzsch (1999), the non-existence of two modeling levels is used as an argument to deny system dynamics models the ability to display emergence. Again, the Gilbert and Troitzsch (1999 p. 12f) quotation:

> "In Table 1.1, the 'number of levels' refers to whether the techniques can model not just one level (the individual or the society), but the interaction between levels. A technique capable of modelling two or more levels is required to investigate emergent phenomena."

From the statement it is difficult to identify what exactly the authors mean to be the missing feature that is responsible for the inability of the system dynamics approach to investigate emergence. Two alternatives are possible:

1. With the system dynamics approach, emergent phenomena *in general* can not be analyzed as two interacting levels can not be modeled.
2. The system dynamics approach can not model two interacting levels *of a social system* –the individual and the society– what results in the inability to investigate emergent *social* phenomena.

The first statement is relatively easy to refute with the help of Forrester's (1968) hierarchy of structure: every system dynamics model, just as every agent-based model, is composed of interacting entities that give rise to macro level system behavior. However, in contrast to an agent-based model, it is not agents, but feedback loops that are the basic building blocks of a system; their interaction can very well give rise to emergent phenomena, as will be shown in the following using an example from literature.

A restriction of the search for examples of emergent phenomena to the simulation oriented literature makes it difficult to find an application that is modeled in the 'language' of system dynamics – differential equations. This is due to the fact that the system dynamics literature does not deal with the concept of emergence. However, by extending the review to authors who are not so much focused on a specific modeling paradigm, but more on the concept of emergence in general such examples can be found. Goldstein (2000) calls the bifurcation of a dynamical system[2] an emergent phenomenon. Newman mentions an example from a similar context: he analyzes the features of a system in the bassin of a strange attractor[3] and comes to the conclusion that this is an example of an emergent phenomenon. Strange attractors fulfill the requirements of not only one, but all the definition alternatives stated above:

- They are unpredictable
- Their behavior is not contained in the behavior of the parts
- They are higher-level constructs

Figure 2 shows a system dynamics version one of the first recognized strange attractors, the Lorentz attractor. Because of the high sensitivity to initial conditions of this analytically not solvable dynamic system the Lorentz equations are often associated with the so-called *butterfly effect*, a statement on chaos that says that the flapping of a butterfly's wings in Brazil can cause a tornado in Texas.

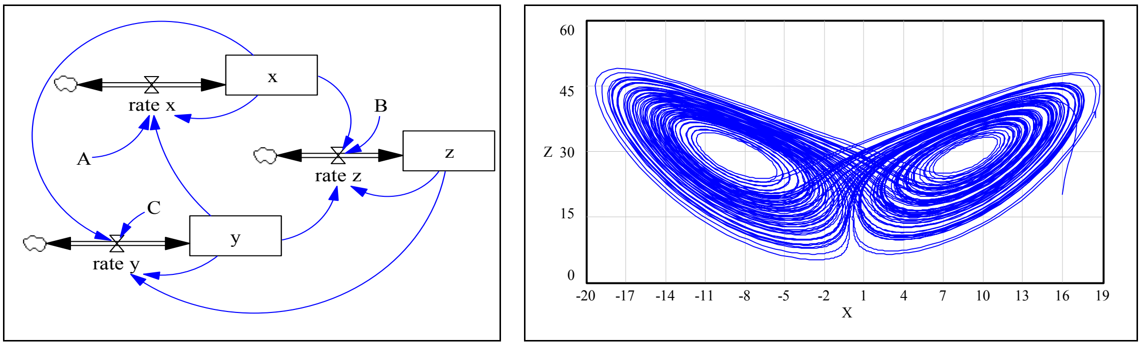

Figure 2: A system dynamics model of the Lorentz Attractor

If the system dynamics approach is capable of modeling emergence in principle, it can be assumed that Gilbert and Troitzsch criticize its inability of modeling two different aggregation levels of a social system. The authors' statement therefore relates to the system dynamics way of assembling a system: interacting feedback loops instead of interacting agents. What Gilbert and Troitzsch do say is that as system dynamics does not model a social system (e.g. a company) by modeling the individual members and that, as emergent social phenomena can only be explained by modeling these individual members and letting them interact, system dynamics is not suited for the analysis of emergent sociological phenomena. This statement contains two assumptions:

1. System dynamics does not model a social system by modeling the individual members
2. Emergent social phenomena are to be explained best by modeling the individual members and their interactions

Many system dynamics models can be found that reject assumption one, probably the most prominent being Forrester's (1961) initial supply chain model that he used to analyze the bullwhip effect: the author models a four-tier supply chain by explicitly modeling every supply chain member, every company. The overall system behavior is then a result of the interaction of the four members. Nevertheless, it is true that the "natural unit of decomposition", as Parunak (1998) calls it, of a system dynamics model is *not* the individual, but the feedback loop. Individual decision makers do appear as intermediate levels of a model, as substructures, if this is required by the problem as in the supply chain case. An agent-based model on the other hand is *always* composed of individuals (that do not necessarily have to be people, but can for example be companies) just like a system dynamics model is always composed of feedback loops. This, for agent-based scholars very unnatural (the world is composed of individuals, why model feedback loops?) approach of assembling a system (Parunak 1998), is a result of the focus on policies instead of individual decisions (Forrester 1961). This different degree of abstraction often leads to a higher level of aggregation of a system dynamics model compared to an agent-based model.

The population model shown in Figure 3, is used to illustrate the differences explained above. In the system dynamics model the dynamics of the overall population is determined by the interaction of two feedback loops, a positive (birth) and a negative one (death), which are influenced by the population characteristics fertility (*BIRTHFACTOR A*) and life expectancy (*DEATHFACTOR A*); depending on loop dominance the population grows or decays. In an agent-based version of the model, it is not the population that has the characteristics fertility and life expectancy, but every member of the population; the population itself is not modeled; it results from the behavior of its members. Each birth or death is then an event affecting the individual, a birth event leading to the rise of a new member (again with individual fertility and life expectancy) and thereby a new system element, a death leading to the exit of a member.

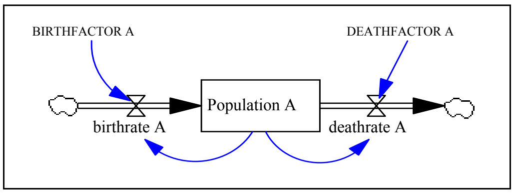

Figure 3: System dynamics model of population dynamics

Thus, in contrast to the agent-based model the system dynamics model does not structurally represent the level of the individual actor. Changes on the individual level are only considered in so far as they affect the population level: as a change in population size; the individual level structure is aggregated and therefore only appears as system behavior. In an agent-based model an event affects both, the system structure (enter or exit of a component) as well as the system behavior.

Altogether, it can be argued that assumption one is true from a methodological point of view. There are system dynamics models that do model individual decision makers, but the individual is not the basic unit of decomposition as exemplified with the help of the population model. Does this result in the inability of system dynamics to analyze emergent social phenomena? The answer to this question (assumption 2) requires an analysis of the concept of emergence in social theory.

In an article about different accounts of emergence in sociology, Sawyer (2001) identifies two theories of emergentism, individualist and collectivist theories. The individualist schools claim that emergent social properties are to be explained by reduction to properties of individuals and their interactions. Even if the overall system properties are not possessed by the parts, they are still reducible to the parts. Collectivists on the other hand, argue that emergent social phenomena exist that can *not* be studied with reductionist methods, as they have no individual-level explanation, although collectivists agree that nothing exists except of the individuals and their interaction. This seeming contradiction is resolved when looking at the argumentation for irreducibility, wild disjunction. Wild disjunction stands for a one-to-many-connection between a high-level property and its lower-level descriptions: one and the same high-level property can be realized by many different lower-level descriptions and these descriptions have no lawful relations with one another. In the case "the relation between higher and lower-level properties is wildly disjunctive beyond some threshold of complexity … the higher-level property [is] not … lawfully reducible." (Sawyer 2001 p. 558) According to Blau (1987 p. 97), examples for such irreducibility can be found in emergent properties of population structures: "It is impossible to trace and dissect the interpersonal relations of many thousands or millions of people, and neither would it be meaningful if all were described".

The above account clearly points at an allocation of the system dynamics and the agent-based simulation approach to the two different schools of emergence in social systems. The agent-based approach models social phenomena by modeling individuals and interactions on a lower level what makes it implicitly taking up an individualist position of emergence (Sawyer 2001); system dynamics, on the other hand, without explicitly referring to the concept of emergence, has a collectivist viewpoint of emergentism, as it tends to model social phenomena on an aggregate system level. Which approach is then the more appropriate one? According to Sawyer (2001 p. 576) there is no universal answer to this question: "…the issue of whether a reductionist or holist approach is appropriate for any given higher-level property or phenomenon is an empirical issue that can only be resolved via scientific inquiry. Before engaging in such study, we cannot know which social properties can be explained through methodological individualism, and we cannot know which are not explainable or predictable in terms of individual-level descriptions."

Coming back to the question in the title: there is no inherent contradiction between system dynamics and the concept of emergence. A study of different phenomena using both, the system dynamics and the agent-based simulation method, could be a starting point for the identification of problem characteristics that point at the use of a specific approach. Maybe we can get to the point that we *do* know whether a reductionist or holist approach is appropriate.

Part II: Does heterogeneity matter? – The case of evolution

To some instance part one already answered the question: there are phenomena that can best be explained by considering the individual agents and their interactions. But, it could be argued from a system dynamics viewpoint, often enough, an aggregation of individuals with similar characteristics results in very similar behavior patterns with the advantage that an aggregate model is a lot easier to analyze and understand – here I again refer to Blau

(1987) who took the large size and complexity of a society as a reason to argue against the reducibility of population structures. Additionally, it could be said that the inclusion of stochastic terms in an aggregated model can display some effects of heterogeneity.

Not only scholars from the agent-based simulation school disagree with the above argumentation. In a 1992 paper titled “Whom or What does the Representative Individual Represent”, Kirman analyzes problem that can arise from neglecting individual heterogeneity in the field of economics and he calls for a more interaction- and individual-oriented approach. Klüver et al. (2003 paragraph 2.5) extend this argumentation to all social systems when they say: “Because the units of social construction – in reality as well as in theory – are social actors … *theoretical* understanding of social dynamics is not possible by just aggregating the collective behavior of many actors.” In the agent-based community the ability to model a high number of heterogeneous agents is therefore considered a feature that makes the approach superior to system dynamics for many social applications (Epstein 1999).

In the following the effects of considering individual differences will be discussed using an extension of the population model described in part one. In the extended model two species compete against each other for resources as depicted in Figure 4. The maximum fertility, expressed by the parameter *BIRTHFACTOR A* resp. *BIRTHFACTOR B* could only theoretically be achieved if the height of the overall population was zero (of course in this case there are no birth). An increase in the overall population reduces the birthrate, as resources become scarcer. The available resources have, however, no effect on the death rate.

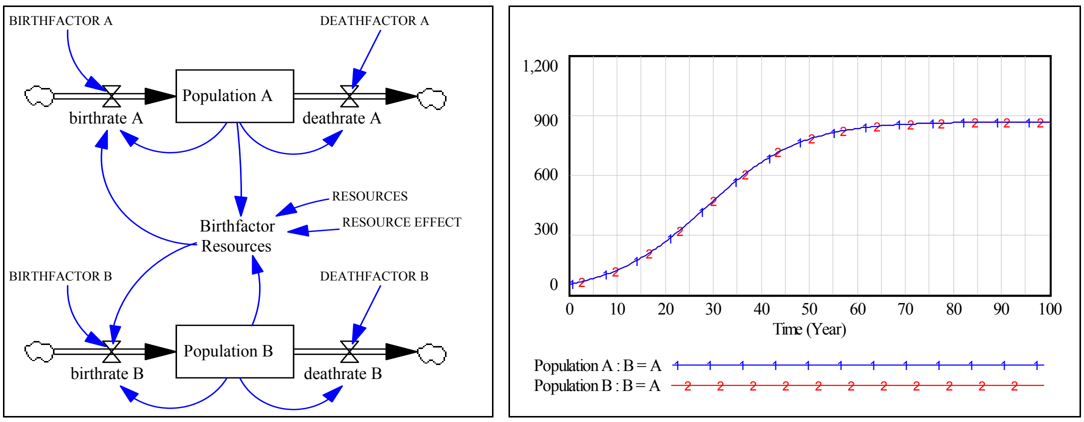

Figure 4: Two Populations competing for resources: system dynamics model

It is evident that in the case the two species have exactly the same characteristics (fertility and life expectancy), as depicted in Figure 4, they will both get the same share of the available resources leading to the same behavior and equilibrium state for *Population A* and *Population B*. If however one species is superior to the other by either having a higher average fertility or a higher average life expectancy, the inferior species will die out, as the opponent consumes all the resources.

In the model displayed in Figure 4 individual differences within one species are neglected; it is assumed that the members are homogenous and act like one entity or that differences that occur over time cancel out each other. Relaxing this assumption can have a considerable impact on population dynamics. In the following the effect of two different stages of a consideration of diversity are discussed using an agent-based version of the model:

1. The relaxation of the assumption that individual differences cancel out each other at every point in time. Here it is assumed that the diversity that exists today has no effect on the future composition of the population.
2. The explicit consideration of the process of evolution where an offspring born with characteristics different from its parents influences the characteristics of its offspring and so on; the assumption of stage one is relaxed.

It was already pointed out in the first part of the paper that the population characteristics fertility and life expectancy are now properties of every single agent. As a deterministic value of these characteristics would mean for every agent to live exactly the same number of years and have –at any point in time– the same number of descendants –a situation that would correspond to the system dynamics model but that would be contradictory to stage one requirements– stochastic terms have to be used for those factors. The resulting agent rules and characteristics are quite simple:

- In a plane of specific size an initial number of members of population A and of population B are randomly placed
- Every agent has a birthprobability and a deathprobability which are modeled using a uniform distribution
- At every time step an agent performs two steps:
    1. If there is some space in its Moore-Neighborhood it reproduces with a probability corresponding to its birthprobability; note that by this rule the local conditions of an agent are important for his fertility – resources (space) are local, not global
    2. It dies with a probability of deathprobability

Using StarLogo 2.1, an agent-based simulation environment developed at the MIT, a possible initial distribution of the agents in the plane and the corresponding distribution after 200 iterations can look like Figure 5 (in the beginning 50 A-agents and 50 B-agents populate the plane; they have exactly the same characteristics). The theoretical overall population maximum determined by the size of the plane equals 2601 agents.

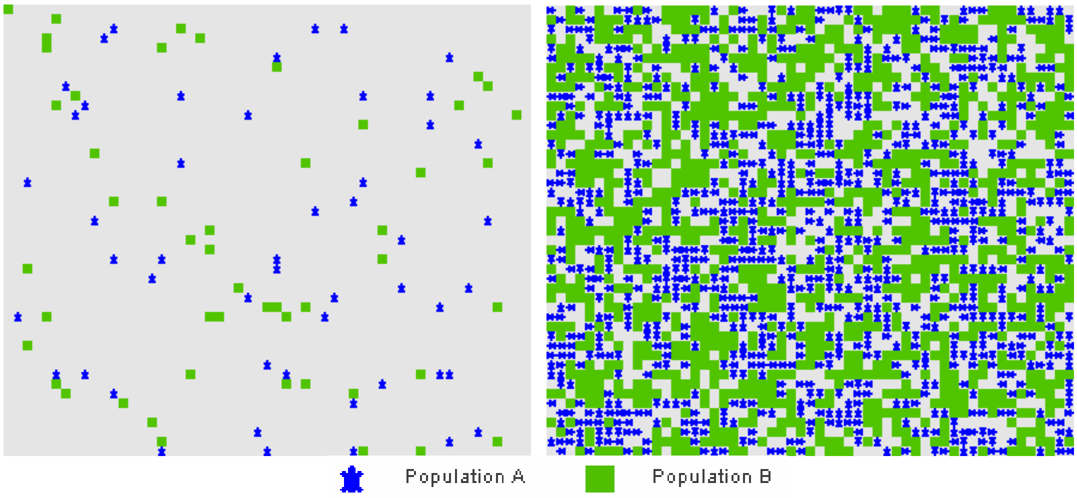

Figure 5: Possible initial agent distribution and corresponding system state in t=200

The term “possible” is important, as in contrast to the system dynamics version the agent-based model, due to its dependence on stochastic variables, neither produces the same output every time it is restarted, nor –in the majority of the cases– generates an equilibrium state: as long as some agents live the fertility and the life expectancy of the overall population depends on stochastic terms with the result of a fluctuation around the equilibrium as depicted in the left graph of Figure 6. In such a case the whole range of possible outcomes of a model of two competing populations with exact the same characteristics goes from A getting extinct by B to A extinguishing B with a situation where both species survive like the one displayed in Figure 5 and Figure 6 (left side) being the most probable.

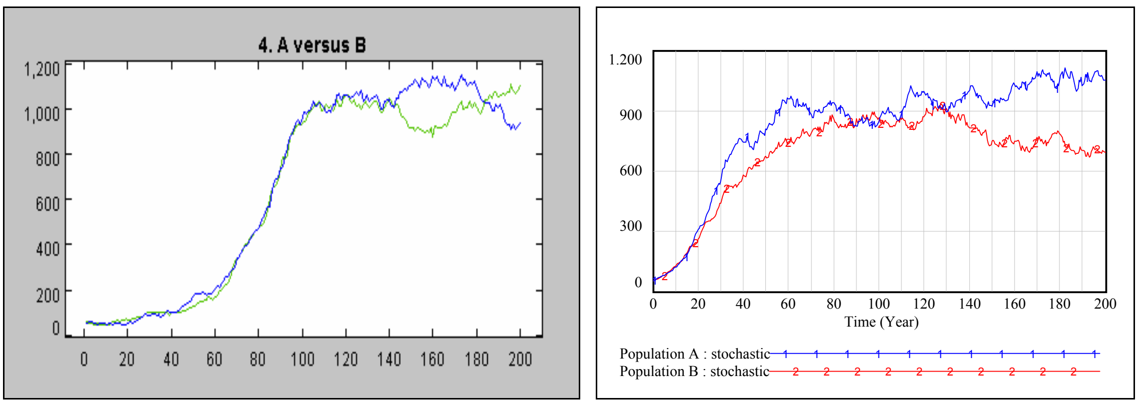

Figure 6: Behavior of A and B – agent-based and system dynamics model

The described effects arising from the stochastic nature of the model can also be obtained using a system dynamics model; the deterministic population characteristics of the model in Figure 4 have to be replaced by a sequence of random numbers, as it has been the case in the right graph of Figure 6. A comparison of the two graphs in Figure 6 reveals that the aggregated system dynamics model is a relatively good approximation of its agent-based counterpart; only the slope is higher in the system dynamics graph. The difference in the slope is an observation that can be made not only in the run depicted above; it results from a different impact of available resources on the birth rate of the population. The problem here is to transform the local decisions made on the agent level to a global policy.

Altogether it can be summarized that a consideration of individual differences, where the diversity that exists today has no effect on the future composition of the population, can be realized with the system dynamics as well as the agent-based simulation approach. The approaches complement one another in the identification of global policies from local decisions.

As explained above the population model as it exists now assumes that the diversity existing today has no effect on the future composition of the population, meaning that the characteristics of a parent generation do not influence the characteristics of their offspring. In the following a relaxation of this assumption is modeled using an agent-based model and the results are discussed. The opportunities and problems of using system dynamics for this study are then treated.

The model described in the following is based on Allen (1988). He builds a mathematical model of two competing populations that evolve over time; this process of evolution takes place by variation of the birth factor, the death factor and the rate of evolution (the fraction of the newborn that is exposed to mutations). Allen finds that small mutations often improve the performance of the overall population, even if they produce a relatively high level of deterioration at any given instant. Allen's basic specifications are transferred into an agent-based model. However, only the birth factor and the death factor are allowed to evolve, the rate of evolution is external; its value has to be defined by the user before starting the simulation.

In order to model the described situation the rules for one of the species, the Bs, are modified slightly: whenever a B agent reproduces itself, only a percentage of its offspring, represented by the parameter *PerfectRepro*, exactly inherits its characteristics, the rest is exposed to mutation that either effects its birthprobability or its deathprobability. The parameter *Deterioration* determines the percentage of the mutations that lead to worse characteristics (a lower birthprobability or a higher deathprobability), the other mutations result in an improvement. To what extent the offspring improves or deteriorates is expressed by the parameter *Mutationfactor*; the extent of change equals a percentage of the parent value (all discussed parameter values can be specified by the user). However, mutations are limited to a specific interval to avoid unrealistic situations like eternal life. The relationship between the parameters that determine the process of evolution is explained in Figure 7 using the example of a parent agent with a birthprobability of 0.3 and a deathprobability 0.2. By multiplying the probabilities along a path, the probability of a descendant with specific characteristics is obtained, e.g. the probability for agent 1 to give birth to agent 23 equals 0.3 * 0.1 * 0.8 * 0.5 at every time step. Note that the possible values of an offspring's birthprobability and deathprobability depend on the actual values of the parent and the value of the *Mutationfactor*; in the example displayed in Figure 7 the *Mutationfactor* equals 10 %.

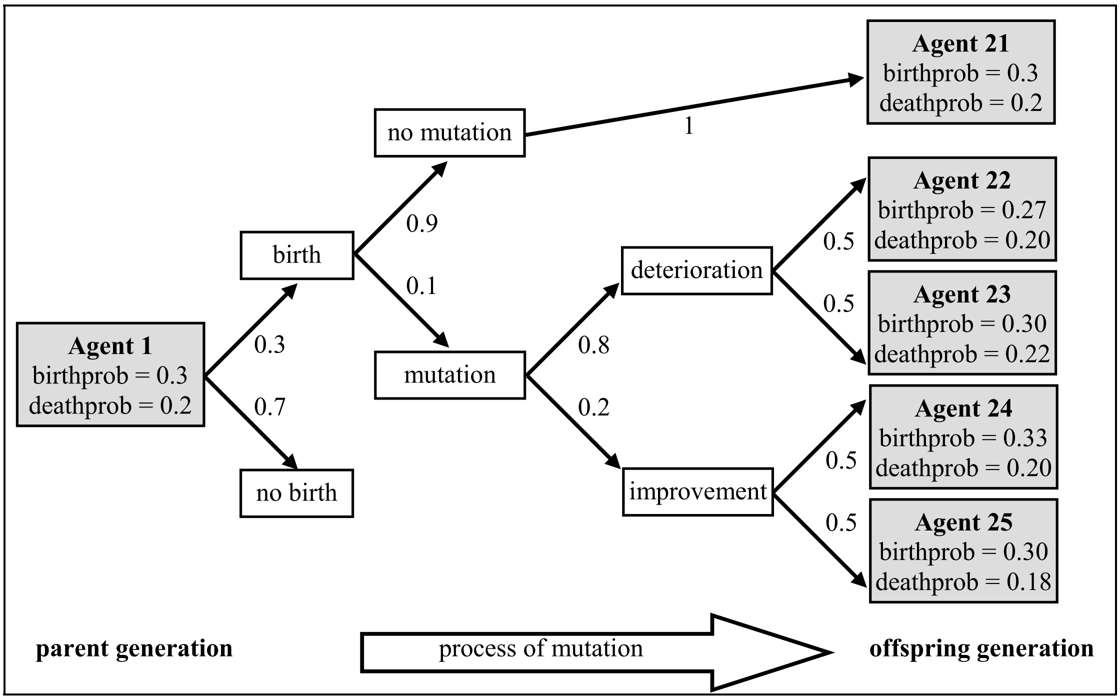

Figure 7: Process of evolution

In the simulation run displayed in Figure 8 the A species having invariable characteristics competes with population B. Initially, both populations have 50 members with exactly the same characteristics (a birthprobability of 0.3 and a deathprobability of 0.2). In comparison to the simulation run above however, the offspring of B is exposed to mutation (the parameter values equal those in Figure 7). The graph shows that despite the fact that mutation leads to deterioration with a very high probability, population B becomes superior to population A after some time; in the long run, population A becomes extinct.

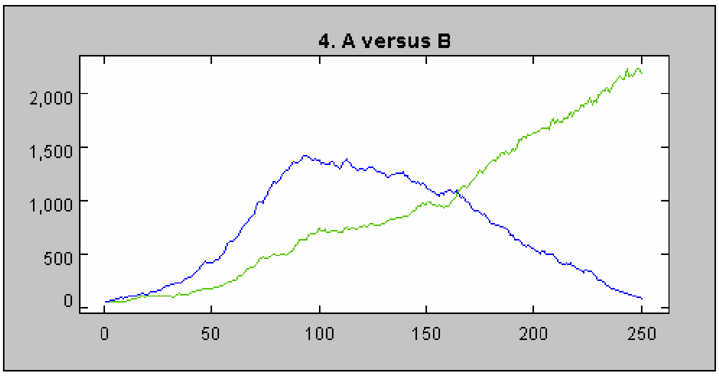

Figure 8: Superiority of population B due to evolution

The behavior can be explained as follows: in the beginning of the simulation deterioration dominates the dynamics of population B; a great part of the offspring is born with less advantageous characteristics than the members of population A; population A leads the race (see Figure 8). However, some mutants are superior to population A. As they have a higher fertility or life expectancy or both, they manage to increase in quantity above average, at the same time the deteriorated population groups can only increase in quantity below average. Therefore the average fertility and life expectancy of the overall population B improves, resulting in an extinction of population A.

It is obvious that the system dynamics model shown in Figure 4 can not be used to analyze this kind of evolutionary dynamics. The question is, if this problem possess characteristics –evolving parameters on the micro level– that make the system dynamics approach inapplicable for its investigation. In the following this question is approached with two attempts to build a system dynamics model with evolutionary population dynamics.

On the basis of the system dynamics model in Figure 4, a very obvious approach to model the process of evolution is to substructure population B using one level variable for every population group –a population group being those members of the population that have the same characteristics. Rates between the levels are then used to model the process of mutation: the flow in a different population group. This attempt is depicted in Figure 9, however, mutation has been limited in that the original population is only allowed to change in eight different ways (two improvement stages and two deterioration stages for the birth- as well as the deathfactor).

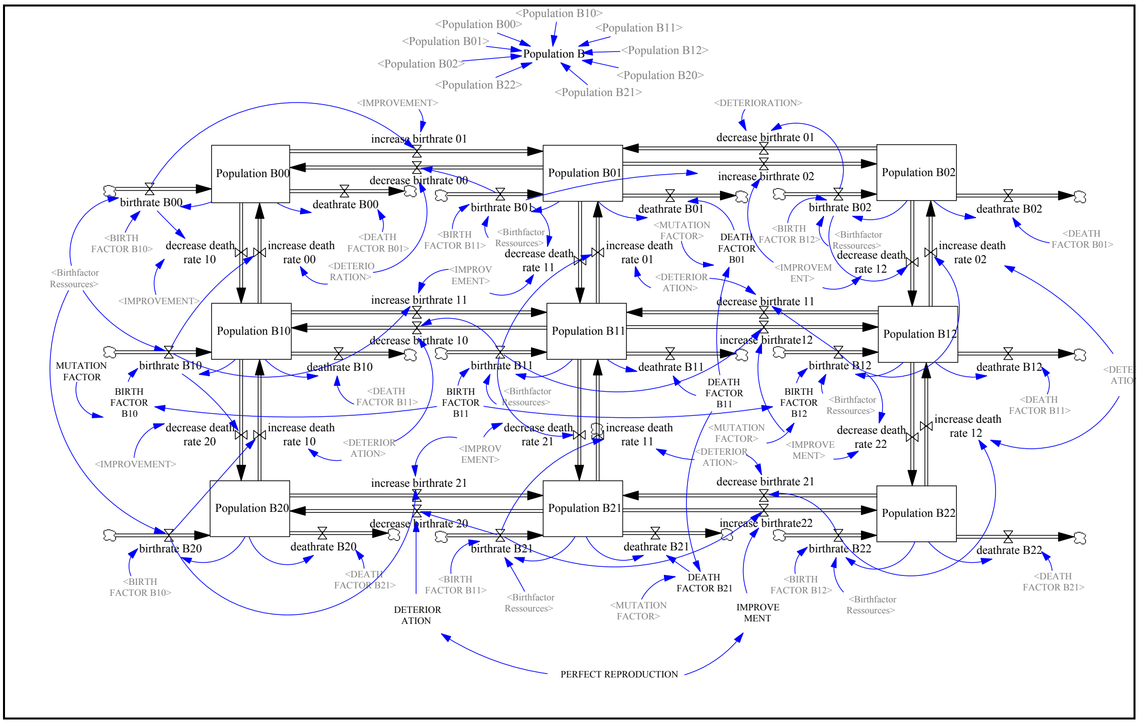

Figure 9: Evolution model for population B – a system dynamics version

The system dynamics model shown in Figure 9 has some severe limitations compared to its agent-based pendant. Despite of the quite complex structure, it allows only for a very limited diversity: in the agent-based model a basically infinite number of population subgroups can evolve through the rule used to model the process of evolution: whenever mutation occurs, it leads to a 10 % improvement or deterioration of either an agent's birthprobability or its deathprobability; in the system dynamics model this number is reduced to nine. A change in the possible number of subgroups requires a structural change of the system dynamics model: level variables as well as the corresponding flows have to be added or deleted (an addition leading to an even more complex structure); in the agent model this can be achieved by a parameter change. It can be followed that the system dynamics approach is inferior to the agent-based approach for this way of approaching the problem.

However, the system dynamics model displayed in Figure 9 is close to a one-to-one transformation of its agent-based counterpart, a fact from which its inferiority could have been expected in advance. The second attempt therefore aims at a more aggregated system-dynamics-like representation of the problem. Again, the model from Figure 4 serves as a starting point; but now, the focus lies not on the evolution of individual agents or population subgroups, but on the process of evolution for the whole population. The corresponding model is depicted in Figure 10.

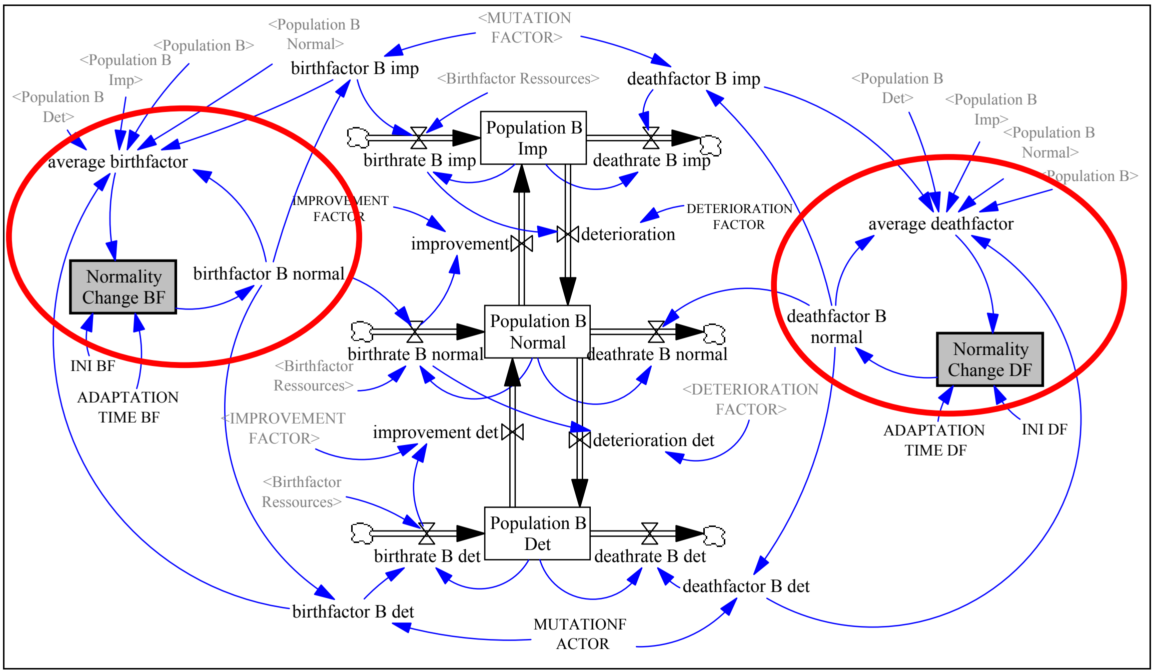

Figure 10: Aggregated model of population evolution – structure population B

The overall population B is composed of three levels: *Population B Normal, Population B Imp* and *Population B Det*; in the beginning of the simulation all members of B belong to the "normal" group, with a birthfactor of 0.3 and a deathfactor of 0.2. However, through the process of mutation, improvement and deterioration of the population characteristics take place modeled through an inflow of part of the newborn into the corresponding levels. So far, the structure is very similar to the one depicted in Figure 9, only that it is even more restricted as only three different subgroups are represented: evolution is synonymous with the split-up of a population to one of the three levels. Now, the structure is extended by the loops involving the delays *Normality Change BF* and *Normality Change DF* (marked by the ellipses in Figure 9): as the *average birthfactor* changes as more an more members of the population move to the improvement or the deterioration level, the *average birthfactor* over time becomes the "normal" birthfactor and this "normal" birthfactor is then the new starting point for mutation. With the help of this structure the limitation of the process of evolution to one or two mutation stages is abolished. A comparison of the behavior of the model, as depicted in Figure 11, with the agent-based model (Figure 8) does show that it is able to reproduce the overall behavior pattern.

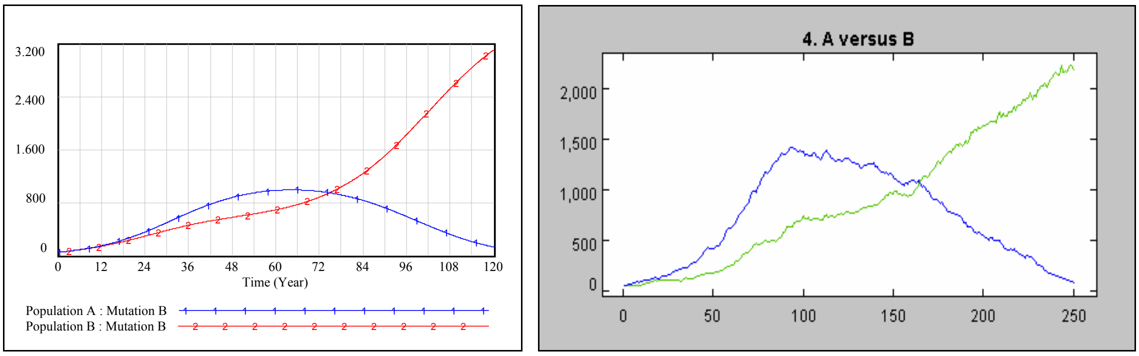

Figure 11: Aggregated versus disaggregated model of population evolution

System Dynamics or Agent-Based Simulation?

The goal of this paper was to show that the question of which method to use for the analysis of a given problem can not simply be answered by: a problem involving a high number of diverse agents is an agent-based problem. Both, system dynamics and agent-based simulation are suitable for a wide range of questions in social systems. One important difference between the approaches is the level of aggregation they impose on a problem and the consequences for system structure and behavior discussed in section one. This could be a starting point for deciding about which of the two approaches to use.

Another decision support would be the amount of information available to estimate causal macro relationships that are necessary for a system dynamics model. The dependence of the birthrate on the available resources is such an example, where a decision rule depending on local conditions has to be transformed into a global relationship. This could be an example where, within a modeling process, an agent-based model of a problem could help quantifying a system dynamics model: Why not stick to the agent-based approach instead of doing both, one could ask. Well, apart from the advantages of significant shorter run-time, the higher level of aggregation as well as the structural representation of the problem under consideration support the use of the model as a communication tool, a feature that becomes especially important when dealing with real-world problems where a client is involved. And, a system dynamics model helps avoiding the problem of not seeing the forest for the trees.

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[1] Mathematically this fact is described by the principle of superposition: assume a time-dependent system S reacts to an input x_1 (t) with an output of y_1 (t) and to an input x_2 (t) with an output of y_2 (t). If the principle of superposition holds, what is equivalent to the linearity of the system, the system reacts to a weighted sum of the two inputs with an addition of the corresponding effects: $S\{k_1 * x_1(t) + k_2 * x_2(t)\} = k_1 * y_1(t) + k_2 * y_2(t)$; k_1 and k_2 are constants.

[2] In the theory of nonlinear systems a bifurcation (lat. *bi* double; *furca* fork) is a qualitative change in the system dynamics caused by a marginal change of the system parameters.

[3] An attractor of a system is the set of all points in the state space (the space that is built by the state variables of a system), that is reached by trajectories within infinite time. A strange attractor is a non-periodic attractor; its points never repeat themselves, but they stay within the same region of the state space.

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