Principles of Emergence - A Generic Framework of Firms as Agent-Based Complex Adaptive Systems

Meike Tilebein
Universität Stuttgart
Institute of Business Administration
Department IV
Keplerstr. 17
D-70174 Stuttgart, Germany

Phone: +49-(0)711-6858 3466
Fax: +49-(0)711-6958 3191
Email: meike.tilebein@bwi.uni-stuttgart.de

Abstract

The concept of emergence is closely related to complexity theory. While this agent-based approach is on its way of becoming a new paradigm in management science, the system dynamics approach is suffering from a lack of management attention, although both are applied to similar problems with similar outcomes. In previous research, scholars have compared system dynamics and agent-based modeling. This paper steps back from the modeling aspect and looks at the requisite conditions, as identified by complexity science, that make emergent phenomena happen in complex adaptive systems. These are agent-based systems that balance emergent efficiency and innovation without central control. We give a comprehensive overview of principles of emergence in such systems and propose a generic framework of these systems for use in management science. This framework then serves to assess exemplary literature applying complexity science to firms and to discuss research implications for both agent-based and system dynamics approaches.

Keywords: complex adaptive systems, emergence, agent-based approach, efficiency, innovation

I. Introduction

Many firms today experience increasingly complex markets and highly dynamic competition. In the face of such turbulent environments, two problems become especially acute: First, these environments make it difficult to manage firms top-down due to time delays and limitations in human information processing capacity. This leads to management science's increased interest in bottom-up approaches. Secondly, firms in dynamically changing environments have to permanently find their way between exploitation of old certainties and exploration of new possibilities [March, 1991].

Balancing these conflicting forces of efficiency and innovation has become a crucial management task in turbulent environments. Management science has not yet come to a final conclusion on how to maintain such a balance.

It could be expected that the efficiency-innovation dilemma calls for application of the generic feedback systems view provided by system dynamics [Senge, 1990]. However, management practitioners and scholars are apparently reluctant to use system dynamics [Warren, 2004]. Instead, looking for a solution to the problems stated above, management scientists and practitioners have recently been showing increasing interest in the field of complexity science [e.g. Stacey, 1995; Brown and Eisenhardt, 1998; Stacey, Griffin and Shaw, 2000, Kappelhoff, 2002; Caldart and Ricart, 2004; the 1999 "Organization Science" Special Issue: Application of Complexity Theory to Organization Science, and the Journal "Emergence", first published in 1999].

This field of research provides an interdisciplinary approach for studying large systems that exhibit emergence. These systems are called complex adaptive systems [Gell-Mann, 1995]. Their prominent characteristic "emergence" describes the generation of macro-level system properties arising from micro-level interactions of system elements without being planned or foreseen [Hodgson, 2000]. This individualist perspective on emergence fundamentally differs from the system dynamics approach, that is also capable of modelling emergent phenomena, but takes a holistic view on emergence [Schieritz and Milling, 2003; Schieritz, 2004].

There are two kinds of emergent properties in complex adaptive systems: spontaneous emergent order due to interactions of system elements, and emergent innovation due to adaptation and evolution over time [Kauffman, 1993]. Combining these emergent properties, complex adaptive systems emergently change, adapt and (co-)evolve in harmony with their changing environments. Hence, balanced emerging properties in terms of order and innovation make a complex adaptive system (CAS) sustainable as a whole although such a system does not have a system-level control.

These characteristics of CASs may account for management science's increasing interest in complexity science, because they address the two urgent problems of managing in turbulent environments: First, emergence in CASs is the result of decentralized, self-organized, bottom-up interaction processes. Secondly, on the basis of these self-organized processes, CASs are sustainable and they manage to maintain an appropriate balance of efficiency and innovation. Furthermore, as there is no system-level control in a CAS, such a system seems to resolve the efficiency-innovation dilemma quite effortlessly, with the permanent balance of these properties being just an unintended by-product of system elements' interactions.

This is why there has been an increasing amount of literature on CAS applications to firms in recent years. These applications cover the entire span of organizational levels and a broad scope of goals. Complexity science uses agent-based approaches to explain the mechanisms of emergence in CASs, as shown in Section II. In Section III, we put these principles of emergence together to form a generic framework of complex adaptive systems in management science. Using this framework we look into different applications of complexity science in Section IV. We analyze the applications' aims and the principles of emergence they use. Typically they address either emergent efficiency or emergent innovation and thus fail to combine, let alone balance, both. We conclude that, while agent-based applications to management science help to uncover the sources and mechanism of emergence in firms, the innovation-efficiency dilemma remains unresolved. As firms, in contrast to CAS models, do have an overall control on different system levels, we suggest a combination of agent-based and system dynamics approaches to capture both individual and aggregated aspects of emergence.

II. Models of Emergence in Complex Adaptive Systems

In this section, we sketch out basic characteristics of complex adaptive systems and prominent models used to study emergence in such systems [Tilebein, 2005; Tilebein, forthcoming]. A CAS is a network of elements whose interactions cause the emergence of overall system level properties. Real examples of complex adaptive systems are ecosystems, bird flocks, ant colonies, the nervous system, or man-made systems like industries or big cities. Although very different in detail, CASs share some common characteristics [see e.g. Holland, 1995; Gell-Mann, 1995; Kauffman, 1993; Auyang, 1998]. CAS Models use agents as basic components [Holland, 1995]. Agents can combine into meta-agents which in turn can form even more aggregated agents. A CAS can be an agent of a network, and so forth: CASs can form a (temporary) structure following a "box-in-a-box" principle [Simon, 1996].

Each agent acts according to an individual set of rules, a so-called schema [Holland, 1995]. Agents in a CAS can be uniform or diverse in their properties and rules. Furthermore, rules and properties can be fixed or agents can be adaptive. In the latter case, the agent's schema contains not only action rules, but also rules for change (that can also be subject to change).

Agents usually have a limited number of direct interaction partners. The self-organization of interacting agents gives rise to emergent phenomena in a CAS. There are two kinds of emergent properties: spontaneous order accounting for efficiency and flexibility, and innovative evolution. Complexity science uses abstract computer-based models to study these emergent phenomena in CASs. Two prominent model types are described in the following.

Models of Emergent Order

Cellular automata are widely used to study the emergence of spontaneous order in rule-based systems. They are computer-based spatial systems of cells that change their state (e.g. black-white) according to a given transformation rule. This rule determines a cell's next state dependent on the actual states of a number of neighbouring cells. In this way spatial patterns unfold over time. Depending on the rules, different static or dynamic patterns emerge. There are four classes of patterns and underlying transformation rules [Wolfram, 1994; Wolfram, 2002], as shown in the examples of an identical first cell row changing under different transformation rules in Figure 1.

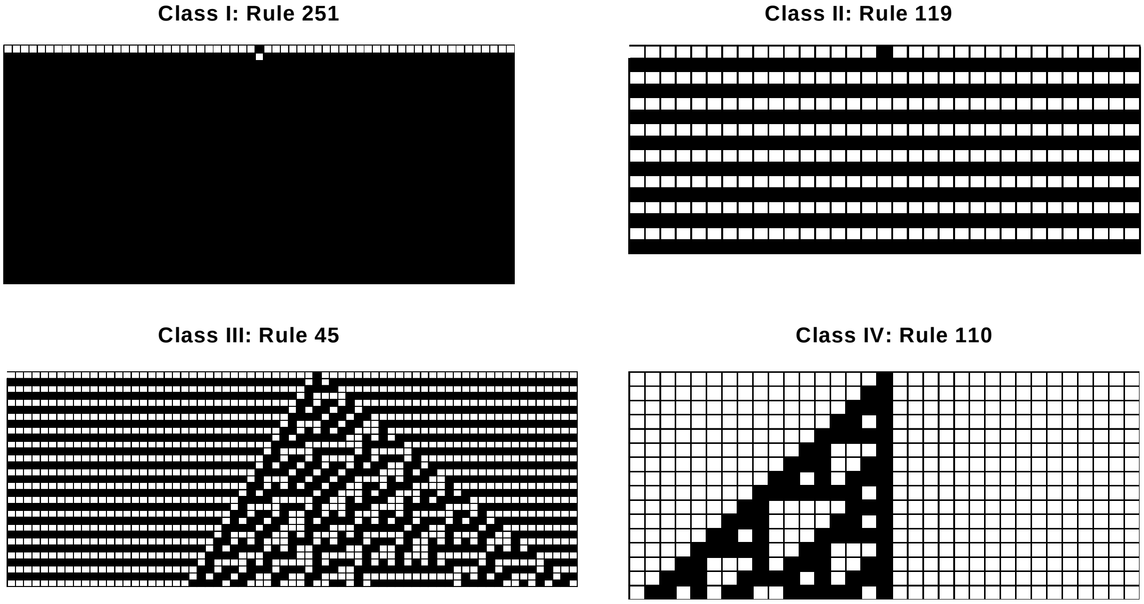


Figure 1. Cellular Automata Representing Four Different Classes
Source: From Wolfram (2002), pp. 55-56

Class I automata turn to stable states, Class II automata show periodic changes, Class III automata generate chaotic, non-periodic patterns and Class IV automata generate complex patterns with changing micro-structures. Class IV automata combine stable structures with dynamics and thus are capable of information processing. From these four patterns, only Class IV automata show emergent flexibility, as their information processing capacity enables them to store information as well as to spread it through the system. This, way, they can respond to changing situations. Their information processing capacity is due to the character of their respective transformation rules that balance connectivity and correlation of subsequent states [Langton, 1992].

Similar insights were drawn from Boolean Networks [Kauffman, 1993], where agents are mutually linked Boolean functions. According to Kauffman, self-organized Boolean networks settle to attractors that can either be chaotic, frozen, or balanced states with both stable clusters and changing regions. In this balanced state on the so-called “edge of chaos”, a network reaches a maximum in information-processing capacity: it can display spontaneous order and absorb external disturbances. The character and diversity of the functions used and the number of their inputs - i.e. the number of interaction partners per agent - determine whether a Boolean network operates on the edge of chaos [Kauffman, 1993].

Another prominent example of a rule-based interaction system is called “boids”. In this computer-based simulation of a bird flock, three rules concerning speed, distance, and relative flight direction control the motion of the individuals, called boids [Reynolds, 1987]. Based upon these rules, boids show bird-like behavior in forming flocks and performing flight maneuvers. Although boids are uniform agents with a fixed set of rules for interaction, the bird flock as a whole can efficiently react to unforeseen disturbances such as obstacles in their path. This kind of emergent order is known as "swarm intelligence" [Bonabeau, Dorigo and Theraulaz, 1999].

Models of Emergent Innovation and (Co-)Evolution

Kauffman provides extensive research on CAS evolution and coevolution using NK-models [Kauffman, 1993]. Agents in these models consist of N elements (e.g. properties, genes, or other attributes). Each element can take on two different values, 0 or 1. To each of the two values of every one of the N elements a fitness contribution is (randomly) assigned. Agents can evolve and improve their overall fitness by switching values of elements one by one, in a process called "adaptive walk". As an alternative, they can perform change processes that allow change of more than one element per step, so-called "long jumps".

A fitness landscape visualizes the overall fitness function. There are three different types of fitness landscapes that are sketched in Figure 2: single-peaked landscapes with one global fitness maximum, multi-peaked landscapes with random peaks, and moderately rugged landscapes with correlated peaks.

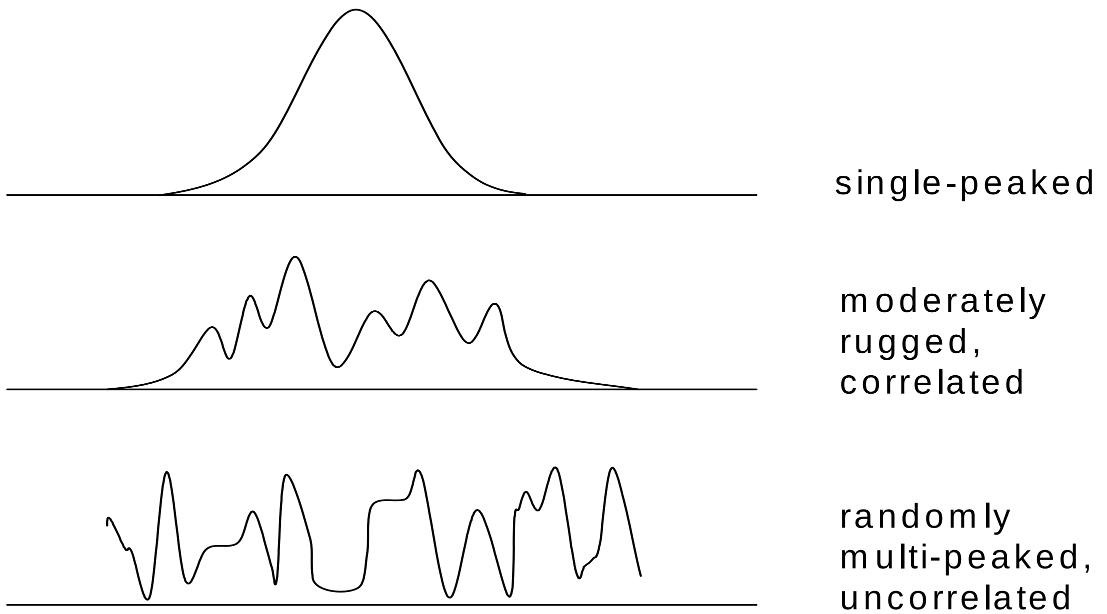
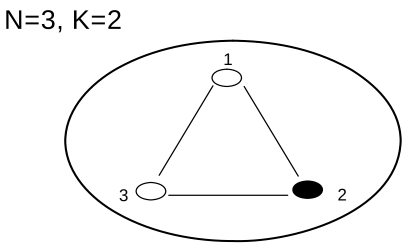


Figure 2. Types of Fitness Landscapes

Adaptive walks are the standard change procedure, whereas long jumps have proven less successful in most situations. Success depends on the type of fitness landscape. As the direction of an adaptive walk has to be by definition uphill, in single-peaked landscapes adaptive walks always lead to the global maximum, whereas in a multi-peaked landscape they end on the local maximum nearest to the starting point. Once the agent has reached a peak it cannot improve any more, although there might be a higher peak in some other region of the fitness landscape. Diversity eventually evolves in a population of formerly identical agents when their random adaptive walks take different directions.

The parameter K in NK-models affects the shape of the fitness landscape. K is the number of epistatic links between the N attributes of an agent, i.e. the number of other elements influencing that attribute. The agent's overall fitness W equals the sum of all N fitness contributions W_i of its N elements. If the fitness contributions are independent (K=0), an element can have two distinct fitness contributions, depending on its state. In this case improvement in one element improves the agent's overall fitness likewise. Thus, a single-peaked fitness landscape is generated. In contrast, if the fitness contribution of one element depends on the value of K others, a single element can have 2^{K+1} different fitness contributions. Switching an element and improving its fitness under these conditions does not necessarily result in overall fitness improvement (e.g. if the agent in Figure 3 switched from 011 to 010, its overall fitness would change for the worse, although the fitness contributions of element 1 and 2 would improve). Thus, a landscape with more peaks is formed (see Figure 3 for a double-peaked fitness landscape). The number of peaks increases with K.



element			fitness contribution			overall fitness
1	2	3	W_1	W_2	W_3	$W = \frac{1}{N}\sum_{i=1}^{N} W_i$
0	0	0	0.6	0.3	0.5	0.47
0	0	1	0.1	0.5	0.9	0.50
0	1	0	0.4	0.8	0.1	0.43
0	1	1	0.3	0.5	0.8	0.53
1	0	0	0.9	0.9	0.7	0.83
1	0	1	0.7	0.2	0.3	0.40
1	1	0	0.6	0.7	0.6	0.63
1	1	1	0.7	0.9	0.5	0.70

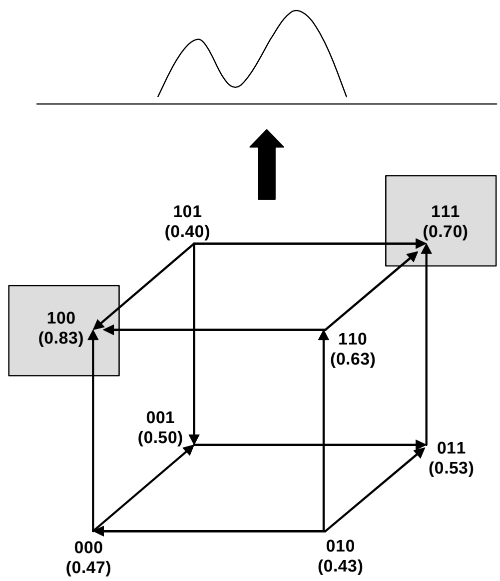


Figure 3. Agent With Double-Peaked Fitness Landscape
Source: following Kauffman (1993), p. 42

Coupling of agents results in coevolution, when evolving agents affect each other. Under co-evolution, an agent's fitness landscape is not static, but may change with every step another agent takes. In other words, the ground is moving, and the agents are forced to permanently innovate. This can be a disadvantage for agents walking in single-peaked landscapes, as they might never reach the moving peak. For agents stalled on lower peaks in multi-peaked landscapes however, a landscape change may move them off that local peak and into a new starting position, ready to explore new innovative paths of development. Therefore, in a coevolutionary scenario, moderately rugged fitness landscapes (K=2) are most advantageous for individual agents [Kauffman, 1993].

To study coevolution, NK-models are extended to NKSC-models, where S is the number of species coevolving and C is the number of links between each pair of species. These parameters determine external complexity, in the same way that K determines internal complexity. Coupled CASs coevolve to the edge of chaos, with a maximum average fitness of agents and a dynamic stability of the overall system, when internal and external complexity are balanced [Kauffman, 1993]. In these systems, emergent innovation of agents continually arises.

III. A Generic Framework of Firms as Complex Adaptive Systems

Complexity science's experiments with evolutionary models, cellular automata, Boolean networks and other rule-based interaction systems reveal that there is a set of characteristic design elements in complex adaptive systems that account for their emergent phenomena. In this section we combine and complement these characteristics in order to propose a generic framework of emergence in CASs for use in management science. This framework [Tilebein, 2005; Tilebein, forthcoming] is more management-oriented than general frameworks of CASs [e.g. Holland, 1995], but more specific than others used in management science [see, e.g. Axelrod and Cohen, 1999; Anderson, 1999].

From the mathematical models outlined in the previous section we can identify seven principles of emergence in CASs:

1. Agents: As stated above, agents are the core elements of complex adaptive systems. When designing a CAS, agents have to be adequately defined. In a general definition, an agent is an active element of a CAS. Agents interact with one another based on a set of rules. In many CAS models, agents are simple switches. In management science, agents' equivalents can range from individuals to firms. Their classification depends on the purpose of CAS applications.

2. Agents' properties: In the models used in complexity science, agents' properties or attributes are often conceptualized as a number of elements that can take on different states or values. CAS models reveal that the number N of elements and the number of links between these elements influence emergence. Relevant properties of agents in business applications depend on the application purpose and the nature of the agents.

3. Action rules: Rules are a prominent part of agents' properties. Action rules describe information processing procedures. In complexity science's models, rules are Boolean functions or other mathematical algorithms. Emergence of order in Boolean networks depends on the character and diversity of the functions used and the number of links between the agents. If these two parameters are set properly, dynamic and flexible structures emerge in a network. Interacting agents can form (temporary) meta-structures, depending on their interaction rules and the number of their interaction partners. These aggregated agents can act as agents themselves. In this way, a CAS shows a "box-in-a-box" structure. In a CAS, all agents' interactions are based on rules. The nature of the rules affects the system's emergent efficiency. In firms, corresponding constructs range from simple if-then rules to mental models in human decision-making.

4. Change rules: Rules, properties and links in a CAS structure can be fixed or subject to changes made by adaptive agents. For agents to be adaptive, change rules have to be defined in order to create variations in agent properties, links and rules. The adaptive walk implemented in evolution processes in NK-models is a change rule that allows agents to change one property at a time in an incremental change procedure. Long jumps on the fitness landscape, on the other hand, describe more radical changes. Depending on the change rules, the results of emergent innovation can be more or less successful in terms of fitness. In firms, if agents are allowed to change on their own initiative, they, too, need change rules. Change is usually restricted in terms of resources, scale, scope etc.

5. Diversity: Agents in a CAS can be uniform or diverse in their properties and rules. Diversity evolves from self-organization when agents are adaptive, with each agent adapting individually to its local network or niche, as in the NK-models. In contrast, diversity can be set by shaping properties and rules of agents in a system where agents are fixed and non-adaptive, as in the "boids" model. If diversity is too high or too low, the information processing capacity of the CAS falls off and efficient order cannot emerge. In firms, diversity evolves from learning and self-organization or diversity is set by shaping agents' properties and rules, for example by staffing teams or by allocating different resources to production lines.

6. External links: The number of external links connecting an agent with others characterizes the density of the resulting network. Experiments with cellular automata and Boolean networks demonstrate that, depending on the density, agents' self-organization processes and the emergence of effects on the overall system level will be either supported or blocked respectively. External links account for coevolutionary dynamics and emergent innovation in a system of coupled adaptive agents. A company's external links include communication links, interfaces in production processes and customer relationships.

7. Internal links: The number of internal or epistatic links is a measure of an agent's internal complexity. When an agent's properties are coupled via internal links, their contributions to the agent's overall fitness are not independent; in this way a change in one property can affect fitness contributions of others. Fitness landscape models are used to characterize change processes of adaptive agents. These agents perform hill-climbing adaptive walks in their individual fitness landscapes, each trying to reach a point of maximum fitness. Depending on the shape of the fitness landscape, which in turn is influenced by internal links within the agent, adaptive walks will be more or less successful. As agents are linked to each other via external links, their fitness landscapes are coupled also. As a result, an agent's fitness landscape becomes dynamic through coevolution. Landscape peaks shift when changes in other agents occur. Internal complexity affects the potential overall system fitness and innovation. Firms can actively design internal complexity, for instance by reducing internal links with the help of product and process modularization. According to the box-in-a-box organization of CASs, the definition of internal and external links depends on the level of observation.

Firms differ from the mathematical CAS models described in the previous section as they do have a system-level control on different organizational levels. Their characteristics are therefore often subject to deliberate intervention rather than random change. This is why we add two principles of emergence to those identified above. First, aggregation of agents is a crucial management task. Whereas agents in CAS models self-organize to form temporary structures and meta-agents, organizational structure in firms is defined and changed by management [Eisenhardt and Brown, 1999; Eisenhardt and Galunic, 2000]. Secondly, fitness landscapes serve as deliberate levers of emergence in firms [Levinthal and Warglien, 1999]. Whereas complexity science assumes fitness landscapes to be randomly set and shaped by internal links, goal-setting is an important activity in management. Hence, we add these two principles.

8. Aggregated agents: In management science such aggregations include departments or networks. In most cases they do not form by themselves, but are defined by management. Their impact on emergence is similar to the agent's.

9. Fitness landscapes: The shape of fitness landscapes affects emergent outcomes of evolutionary and coevolutionary processes, as discussed with external and internal links. Fitness landscapes in management science include incentive systems or performance measurement systems. In addition, organizations can affect their own fitness landscapes by establishing external links to partners and competitors and by designing internal complexity.

Figure 4 gives an overview of the resulting framework of firms as complex adaptive systems with nine principles of emergence.

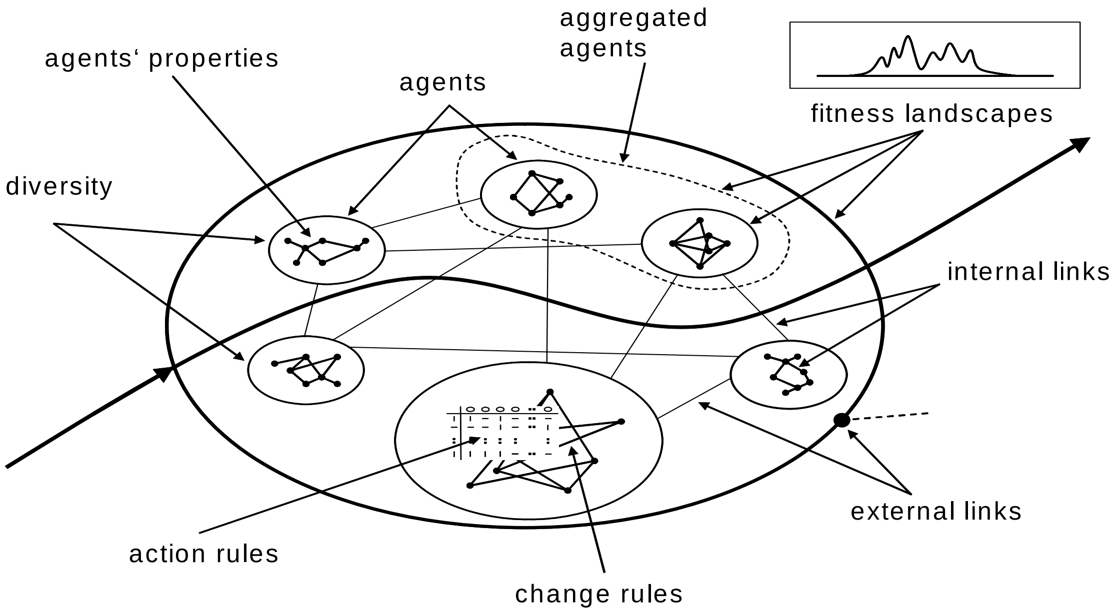


Figure 4. A Generic Framework of a CAS's Principles of Emergence

IV. Using the Generic Framework to Analyze Business Applications of Complex Adaptive Systems

CAS principles have been applied to a number of management science problems on different organizational levels, ranging from individual to industry level. Besides the differences in application levels there are also differences in objectives: whereas some of the transfer concepts aim at emergence of efficiency and flexibility, others aim at emergent evolutionary innovation. In the following we distinguish four organizational levels – the individual resource level, the organizational sub-unit level, the firm level and the network level. Starting with the individual level, for each level we examine at least two exemplary applications of CAS principles with different objectives [Tilebein, 2005; Tilebein, forthcoming]. We focus on the questions what the desired emergent phenomena are and which of the principles of emergence the applications employ.

Individual Level

On the individual resource level, insights from CASs are adopted to explain the emergence of knowledge, culture or meaning. For instance the so-called "memes" [Dawkins, 1989], which are society's equivalent for genes, can be seen as agents that interact to build culture or knowledge. Agents can be, for example, ideas, scientific theories or pieces of music. They are located in individuals where they compete for attention [Marion, 1999; Blackmore, 2001]. This concept is based on the diversity of agents and on selective fitness landscapes as principles of emergence.

The concept of complex responsive processes [Stacey, 2001] focuses on the interaction processes that enhance the emergence of knowledge. Agents are elements of knowledge, called symbols. Meaning is ascribed to these symbols via interaction and communication processes. In this view, knowledge is an emergent property of a communication process. Rules and internal links are the principles of emergence of CASs addressed by this concept.

Organizational Sub-Unit Level

On the organizational sub-unit level, there are some concepts that aim at emergent order and others that aim at emergent innovation. Applications aiming at emergent order and efficiency use swarm intelligence and agent-based systems [Bonabeau, Dorigo and Theraulaz, 1999; Macready and Meyer, 1999; Bonabeau and Theraulaz, 2000]. The basic idea is to provide agents (these can be software representations of technical resources of any kind, or even humans) with a fixed set of rules and objectives for their interaction, and then allow them to self-organize according to the rules given. Properly set, the overall system will display emergent order, it will be robust in the face of disturbances and it will be able to respond to unforeseen changes. Swarm intelligence is used in resource allocation processes to replace conventional optimization procedures that are of limited use when faced with dynamically changing problems. In these concepts, agents and their properties as well as action rules serve as design principles.

Aiming at emergent innovation, Allen uses coevolutionary simulation models to study emergence of knowledge and innovation [Allen, 1997; Allen, 2001]. Agents in these models can be either individuals or groups. Allen stresses the fact that learning opportunities and mistakes are sources of innovation when communication structures are shaped properly. In terms of principles of emergence, the concept thus focuses on diversity, external links and change rules.

Firm Level

On the firm level, there are applications similar to those on the sub-unit level that use agent-based systems to efficiently manage production processes. Correspondingly, principles of emergence are agents with their properties and action rules. One application, for example, dynamically restructures a production-process layout using an agent-based system with mobile resources as agents [Wiendahl and Harms, 2001].

However, most of the firm-level applications aim at emergent innovation, for example in strategies, technologies, projects or organizational knowledge. Often they use NK-models [Caldart and Ricart, 2004]. One exemplary application links the emergence of strategies to organizational structure and information processing [Boisot and Child, 1999; Boisot, 2000]. This concept utilizes diversity (cognitive complexity) and internal links (relational complexity) as principles of emergence.

Network or Industry Level

On the network level, applications use agent-based technologies to improve efficiency of interorganizational production and supply chain management [e.g. Dangelmaier et al., 2002]. Other order-oriented applications analyze the emergence of industrial districts [Rullani, 2002]. Agents are firms in all of these applications, and the emergent results of their interactions are efficient processes or structures. Action rules, external links and fitness landscapes serve as principles of emergence.

In addition, CAS models aimed at innovation are used on this level to foster competitive advantage. In a model-based application, Kauffman's NKSC-studies are applied to firms in coevolving networks [McKelvey, 1999], with a focus on balancing internal and external links as principles of emergence.

V. Discussion and Conclusions

Firms in turbulent environments face two problems: They have to permanently balance the conflicting forces of efficiency and innovation, and they have difficulties in achieving this balance by using central control mechanisms and top-down processes. CASs exhibit both efficient emergent order and emergent innovative evolution. A balance of these emergent qualities in agent-based CASs results from decentralized interactions of agents without being planned or foreseen. As these characteristics of CASs seem to perfectly match the requirements of firms in today's turbulent environments, management science has recently been showing increasing interest in this agent-based approach and the requisite conditions under which emergent properties arise in CASs.

Abstract mathematical models reveal the principles of emergence in CASs. These are interdependent characteristics of complex adaptive systems and their agents. The interplay of these characteristics under certain conditions can give rise to emergent phenomena on the system level. In this paper we sketched out basic ideas of CASs and proposed a generic framework of firms as complex adaptive systems. We then used this framework to analyze exemplary applications of CAS principles to different organizational levels in firms. From this analysis we note two aspects in favour of a further CAS-based approach to emergent phenomena in firms:

1. CASs can contribute to a deeper and more integrative understanding of the multiple issues involved in emergence of balanced innovation and efficiency on all organizational levels.

2. Applications of CAS principles already exist for different organizational levels and specific problems.

These findings from our analysis suggest that complexity science helps to uncover the sources of emergence in firms, but applications are still disparate. Agent-based approaches derived from complexity science are not yet ready to offer a comprehensive solution to the two problems of firms in turbulent environments for three reasons:

1. Whereas in theory a CAS should be capable of both emergent order and emergent innovation, concepts transferring these findings into firms are fragmented into two basic streams. One stream attempts to make use of the efficient self-ordering properties of complex adaptive systems. Examples include applications of swarm intelligence and agent-based technologies. A second stream is based on NK-models and strives to transfer insights concerning coevolution and emergent innovation of CASs to different organizational levels.

2. Each application employs only a few of the principles of emergence identified in our generic framework. None of them thus makes use of the full potential of a CAS.

3. There are no multi-level models so far that could reflect real bottom-up processes. CAS applications span a wide range of organizational levels. However, most applications take into account only two organizational levels: one agent level and another level where the respective emergent properties arise, be it emergent innovation or emergent order

Despite of these evident shortcomings of CAS applications, ideas from complexity science and agent-based emergence are rather popular amongst management scholars and practitioners. It has been stated that the most popular methods used in strategy- and policy-making show at least one of the following four characteristics: They consist of simple principles that are open to wide interpretation; they cause substantial changes to business operations or configuration; they provide substantially new management control approaches or they offer problem-solving methods [Warren, 2004]. The CAS perspective on firms seems to fit in the first two categories: It offers a new agent-based approach to firms that is based on simple principles and the metaphor of the emergent “edge of chaos”, and this perspective causes a change in focus from the whole to the individual. This could explain the increasing popularity of agent-based approaches.

However, when agent-based approaches are applied to firms, the nature of these approaches implies that the relations between sources of emergence and emergent outcomes remain obscure. Consequently, learning from these applications that are based on individual agents’ behaviors is rather difficult. In contrast, the system-dynamics approach applying an aggregated and feedback-structure view, provides a good basis for learning. This is why we suggest that system dynamics modeling, with its characteristics as a policytesting and problem-solving method [Warren, 2004], should be combined with agent-based approaches to enhance understanding of emergent phenomena. Existing models integrating agent-based and system dynamics approaches show that such hybrid modelling can combine the advantages of both approaches [Schieritz and Größler, 2003; Rahmanandad, 2004].

We conclude that complexity science's agent-based approaches are far from generating a ready-to-use concept for solving the acute problems of firms in turbulent environments. However, insights into CASs can reveal the conditions necessary to manage the conflicting forces of efficient operations and innovative development in today's business environments with the help of emergent effects. Efforts towards integration of agent-based and system dynamics approaches should be undertaken in order to enable and support these processes of emergence in firms and to gain a deeper understanding of the principles of emergence.

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