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Through the Looking Glass of Complexity: The Dynamics of Organizations as Adaptive and Evolving Systems

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Abstract

This paper examines how organization theory can benefit from advances made in the interdisciplinary field of complex systems theory (CST). Complex systems theory is not so much a single theory as a perspective for conceptualizing and modeling dynamic systems. The field of complexity is described in terms of the characteristics of systems that are typically the subject of its study, the type of analytical tools used by researchers in this field, and the recurring paradigms that characterize this research perspective. The concepts of self-organized criticality and self-organization and their relevance to organizational studies are examined. The potential usefulness of these concepts is illustrated in the context of organizational evolution and social network analysis. An alternative model of organizational evolution, based on biological evolution, is proposed and propositions are developed. Unlike traditional models for organization, this model does not rely on an algorithm of optimization of a fitness function. The problem of self-organization is approached from the viewpoint of random graph theory and is applied to the analysis of social networks. Finally, important issues in using concepts from the field of CST are discussed. It is suggested that the immediate benefits of CST may be as a framework that facilitates conceptual elaborations and encourages formal modeling; both activities may provide fresh and deep insights into organizational phenomena.

(*Complex Systems Theory*; *Computer Simulations*; *Organizational Evolution*; *Organizational Adaptation*; *Social Network Analysis*)

Introduction

The tradition of viewing organizations as systems has had a long intellectual history in organizational theory (Katz and Kahn 1966, Ashby 1968). For decades, organization theorists have invoked concepts from general systems theory such as homeostasis, cybernetic control, and dynamic equilibrium to describe organizational phenomena such as stability and adaptation. Organizations are now routinely viewed as dynamic systems of adaptation and evolution that contain multiple parts which interact with one another and the environment. Such a representation is so common that it has acquired the status of a self-evident fact. Yet the profound implications of such a viewpoint for theory and analysis have not been adequately examined or exploited. Specifically, any representation of organizations as dynamic systems of adaptation and evolution implicitly assumes that organizations are "complex systems" as described by scholars in the emerging multidisciplinary field of complex systems theory (CST). In this paper we propose that by explicitly recognizing the complex system characteristics of organizations and pursuing their implications, organization theory (OT) can profit from the advances made in the field of CST.

The interface between OT and CST is in many ways natural and inevitable. At an abstract level, OT and CST grapple with similar conceptual issues such as dynamic change, adaptation, and evolution in complex systems. They seek answers for similar questions such as naturally occurring patterns in systems, emergence of new forms, etc. (Stacey 1995; Cheng and Van de Van 1996, Brown and Eisenhardt 1997). In this paper, we are primarily concerned with how OT can benefit from work done in CST.

Some introductory remarks about CST are in order. First, complex systems theory is not so much a theory as a perspective for theorizing and modeling dynamic systems. By cultivating this perspective, organization theorists can enhance their conceptual and analytical tool kit in significant ways. Second, just as CST is not a single theory, it would be wrong to think of CST as a set of mathematical recipes or preexisting algorithms that can be applied directly to OT. The interface between CST and

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OT is more complicated. As we will show, reconceptualization of organizational phenomena has to precede the application of CST to OT. The potential benefits of taking a CST viewpoint of organizations is as much theoretical as it is analytical.

We begin by attempting the challenging task of characterizing CST. CST is not so much a theory as a heterogeneous ensemble of often exciting but not always polished mathematical observations, beyond the confines of local analysis. Our aim is not to present an exhaustive coverage of CST. Rather our aim is to identify CST paradigms that are especially relevant to the study of organizational phenomena. On this basis, four areas of CST are given preferred attention—complex adaptive systems, self-similarity, self-organized criticality, and self-organization. We discuss each of these concepts in detail and illustrate their applicability to OT. Following this, we demonstrate the usefulness of adopting a CST perspective by turning to two important areas in OT—evolution of organizational forms and social network analysis. In each instance, we use CST to develop new propositions and models of the focal phenomenon. We hope that these examples will serve to provoke interest in this fertile and unexplored area of research.

Complex Systems Theory

CST is a highly interdisciplinary research perspective. Its intellectual roots can be traced back to the early history of mathematics, linguistics, economics, and biology (Schroeder, 1990). Regardless of their disciplinary affiliations, researchers who use a CST perspective share a common fascination for the new insights into the dynamics of systems that are made possible by the advent of powerful computers. The emergence of CST as an important research perspective owes much to the phenomenal increase in the processing capacity of computers. The increased capacity enables the exploration, though numerical techniques, of the dynamic content of nonlinear systems beyond the limits of local analysis.

As CST is more of a research perspective than a single unified theory, the option of presenting the basic assumptions and tenets of a theory is not available. A more appropriate way of introducing CST is to describe the different facets of this perspective. Accordingly, we describe CST from three viewpoints—the characteristics of systems studied by CST researchers, the analytical tools used to study these systems, and the dominant paradigms that characterize the CST approach.

Characteristics of Complex Systems

Although CST deals with complex systems, there is no universally accepted or clearly articulated definition of the concept of complexity in CST. This problem is not unique to CST however. The concept of complexity seems inherently problematic as it is used to mean different things in different fields. Even within the same field it often connotes different things. Take the example of task systems in OT. It is generally agreed that the complexity of a task system is an important feature that has a significant bearing on the performance of the task system. However, there is little agreement on the definition of the term complexity. It is used to refer to the number of elements in a task, the degree to which the task is programmable, the number of exceptions in the processes, etc. (Scott 1992, p 229).

As it turns out, this multiplicity in meanings is not a problem for CST. Like organizations, complex systems are difficult to define but easy to recognize. In order to describe complex systems, we take a fuzzy set approach. Complex systems may be seen as exhibiting any of a set of basic characteristics. We will consider two commonly observed characteristics of complex systems: large number of interacting elements and emergent properties.

Large Number of Interacting Elements. Complex systems tend to be made up of a large number of elements that interact with one another. Such interactions are typically associated with the presence of feedback mechanisms in the system. These interactions in turn introduce nonlinearities in the dynamics of the system. The elements that make up a system could be atoms, sand particles, machines, people, etc. A complex system can be made of diverse types of elements. The system can a priori be as heterogeneous as the modeler may desire. But the tendency is to try to elicit complex behavior out of simple rules or interesting emerging properties which are not natural extensions of the rules of interactions. Parsimony is therefore often considered a blessing. Organizations are complex systems in that they are made up of individuals, groups, and departments that interact with one another by way of feedback mechanisms.

Emergent Properties. In addition to the presence of a large number of interacting components, complex systems often exhibit "emergent properties," i.e., the appearance of patterns which are due to the collective behavior of the components of the system. These patterns are not to be confused with the well-known ability of the human mind to detect patterns even when the data is random. The emergent properties we refer to are independently observable and empirically verifiable patterns. A commonly cited example of an emergent property in physics is the temperature or pressure of a gas, modeled as emerging from a large number of molecules hitting each other. An example of emergent property that is relevant to OT is the distribution of size of business firms in an economy. If one plots the size of the largest firms (by assets or number of employees) as a function of their rank order, in a log-log plot, it will approximate a straight line with slope close to -1 (Simon 1955).[1] This is a very robust observation, in that it is true today just as it was four decades back. The appearance of this regularity is an example of emergent property because its origin is mysterious and cannot be easily explained by modeling the individual firms. Later in this paper we re-examine this observation from a CST point of view. The main features of the characteristics discussed so far are summarized in Table 1.

While the above characteristics are commonly observed, the concept of chaos is also often associated with complex systems. However, this is difficult to justify. Although the concept of chaos has played an important role in the sociology and history of CST, it corresponds to a different field. Chaos does not refer to a class of systems, but to the dynamic behavior of a large class of nonlinear systems characterized by high sensitivity to initial conditions (May 1976, Jackson 1993, Devaney 1989). Complex systems do not need to be chaotic to be "complex," and chaos is not closely related to complexity. In other words, "chaos cannot explain complexity" (Bak 1996, p. 31). For example, an emergent property like self-organized criticality, which we will discuss at length, corresponds to a dynamic state, different from chaos. This is not to say that the concept of chaos may not be useful for OT (see Thietart and Forgues (1995) for a discussion of the potential usefulness of the ideas underlying chaos for organizational theory). Mathematical chaos suggests that simple models can have very complex dynamics. Research in CST on the other hand suggests that complex models may exhibit very simple dynamics. It is in this latter way that CST is most useful in the study of organizations.

Analytical Tools Used in CST

A second way of characterizing CST is to consider the analytic tools used by researchers in this area. CST relies heavily on the use of mathematical modeling and computer simulations to study the dynamics of complex systems. Cellular automata (CA) are particularly useful analytical tools used by CST (Wolfram 1984). CA are a class of computer simulations. Their most useful feature is that with simple rules, they can reveal complex behavior. The ingredients of a typical simulation are a certain number (which can be large) of interactive agents and a set of rules of interactions between agents. Starting with some initial condition, the simulation consists in applying the rules through several iterations. The famous game of life of Conway (Berelamp et al. 1982) is an example of cellular automata[2] with simple rules, few components, and a rich dynamic content (Bak et al. 1989). CA are very versatile tools that can also be applied to the study of pattern formation, artificial life (Adami 1998), fluid dynamics, etc.

The book *The Evolution of Cooperation* (Axelrod 1983) has inspired a fruitful line of research that uses CA to model societies. The rules of interaction between agents tend to be based on game theory, like tit for tat or prisoner's dilemma (Nowak and Sigmund 1992). This approach has also been used to study the economic organization of a system of agents having very simple rules of behavior and interaction (Epstein and Axtell, 1996). A

Table 1 Characteristics of Complex Systems

CST Concept	Description	Examples/Applications
Self-Organized Criticality (SOC)	Dynamical state of a complex system main signature: "1/flaw"	Ubiquitous Famous examples: • Sandpile CA • Punctuated equilibria
Self-Organization	Spontaneous creation of complex structure as a result of the dynamics of the system	• Biological evolution • Emergence of hierarchies
Complex Adaptive Systems (CAS)	CA made of interactive adaptive agents	Used to "explain" self-organization or study communities of intelligent agents
Cellular Automata (CA)	Computer simulation technique using a grid (discretized space), interactive components, and iterative rules of evolution (discretized time)	Wide range of applications: • Artificial life • Communities • Laboratory to study emergent properties

major attraction of CA in such analysis is that they provide a good laboratory in which to elicit emergent properties (Forrest 1991).

CST Paradigms

The final and perhaps the most useful way of characterizing CST is to identify the recurring paradigms that dominate research approaches in this area. Etymologically a paradigm is an example of a rule. We use the term "paradigm" to refer to examples in a sense similar to Kuhn (1962) where it denotes a set of concepts or systems of explanations shared by the members of a scientific community. These paradigms convey the new perspectives that CST may bring to the study of dynamic behavior of organizational systems. In the following section, we discuss some CST paradigms that are potentially relevant and useful to OT: complex adaptive systems, self-similarity and fractals, self-organized criticality, and self-organization.

Complex Adaptive Systems (CAS). CAS represents a class of complex systems which has great potential for OT. Using this paradigm, CST researchers model systems as being composed of interactive adaptive agents. The complexity results from the adaptive behavior of the agents (Holland 1995). CAS is potentially useful in studying important organizational phenomena such as the emergence of hierarchies (Simon 1973) and self-organization. A simple example of CAS would be many amino acids building a protein. A complicated example would be many chemical and biochemical compounds building a cell. In both cases the result is an aggregate with very different properties from its parts, and in the case of the cell, also an adaptive agent.

One weakness of CAS as a paradigm for understanding self-organization is that the adaptive behavior of the agents is an input, and the physics of the self-organization is buried in the assumptions. Seen from the perspective of physics, self-organization requires a mix of conditions like being out of equilibrium (Nicolis and Prigogine 1977), and the dynamic possibility of building new stable dynamic units made from the aggregation of several components. The adaptive nature of the agent is what a physicist would like to "explain," not assume.

Self-Similarity and Fractals. CST researchers often look for evidence of self-similarity in the systems that they study. Self-similarity means that at some level of abstraction, the system exhibits invariance under a change of scale. In other words, the functional relationships between different subsystems in a system are similar to the relationships between elements in each subsystem. One example of self-similarity in OT is suggested by Lomi and Larsen (1996). Using a computational model, they point out that population ecology studies in OT find similar results for density-dependence whether the study focuses on a city (e.g., Baum and Mezias 1992) or an industry (Hannan et al. 1995).

Fractals are the most common and powerful mathematical tool to analyze self-similarity (Mandelbrot 1982). Fractals are mathematical spaces. They are called fractals because their "dimension," computed according to specific rules, is not an integer. Fractals were originally invented or discovered by Mandelbrot a few decades ago. They are pervasive in nature such as the shape of coast lines and ferns (Barnsley 1988). Fractals and multifractals are an important part of the culture of CST (Feder 1988). They seem to have an unlimited realm of applications (Pickover 1996), from percolation and fractures to crystal growth and diffusion limited aggregation (Bunde and Havlin 1991).

The relation between self-similarity and fractals stems from the way fractals are often built. They can be the result of iterating an infinite number of times the same operations or maps (Barnsley 1988). These operations do not have to be linear. As a result, the fractals are by construction invariant under those maps. The invariance under a linear map, like a change of scale which is the basis for self-similarity, is therefore characteristic of a fractal. In the context of OT, this kind of approach could consist in detecting or suspecting similarities between different scales and building a mathematical object to represent it, which can be used to establish in a quantitative way that fractals can be used to model this self-similarity. This is an area of great significance to OT as the issue of cross-level analysis is a recurring theme (for example, research on the relationships between individual learning, group level learning, and organizational level learning (Cohen 1996)).

Self-Organized Criticality (SOC). SOC is an intriguing dynamic concept which seems to be so ubiquitous in complex systems that Bak (1996) tends to identify SOC with complexity or to treat SOC as a basic feature of complex systems. The concept of SOC is best understood by turning to two widely studied examples in the CST literature—sandpile cellular automata (Christensen et al. 1991) and punctuated equilibria (Bak and Sneppen 1993).

The sandpile cellular automata attempts to model the behavior of a sandpile. However, it is not a model of a realistic sandpile. It is a CA where grains of sand fall one by one on the ground, building a cone. The cone becomes steeper and steeper up until the moment where the slope reaches a critical value. Adding more grains of sand leads to avalanches. One can show on computer simulations that the frequency of the avalanches is inversely proportional to their size (this is referred to as the 1/f law). The system is then "Self-Organized Critical."

Studies of punctuated equilibria model the progress of biological evolution (Gould and Elridge 1977, Gould 1989). In this case the models capture a well-known feature of biological evolution—it does not proceed smoothly. There are periods of fast evolution between long moments of stagnation. In this example, the evidence of SOC is the fact that the frequency of the periods of large evolutionary activity is inversely proportional to the size of the evolutionary activity. Once again, this distribution follows the 1/f law.

The evidence of SOC or its most conspicuous signature is the so-called 1/f law (which in fact means $1/f^a$, $a < 2$). 1/f distributions are a ubiquitous phenomenon which is found in physics (Press 1978), quasars, river flows, brain activity, size distribution of business firms (Ijiri and Simon 1977), earthquakes (Gutenberg and Richter 1956, Sornette 1994), biological evolution, linguistics (Zipf 1949), etc. SOC is an emergent property which may, in some cases, correspond to a dynamic optimization. For example, the heart is healthiest, i.e., it has the highest level of adaptability, when the heart rate has a 1/f power spectrum (Kobayashi and Misha 1982, Goldberger and Rigney 1990).

The apparent universality of the 1/f law may reflect the ubiquity of SOC, although the reason for it is still mysterious. SOC is a problematic concept. As the two examples of the sandpile CA and punctuated equilibria suggest, it seems to cover different types of dynamic situations. The SOC displayed in sandpile cellular automata corresponds to a dynamic equilibrium resulting from the combined effect of a linear instability (the slope of the cone getting steeper than the critical value), and a nonlinear feedback or dissipation (avalanches). In the case of punctuated equilibria, SOC does not reflect a dynamic equilibrium but is part of the dynamics of change. To be able to differentiate between different types of dynamic situations, conceptual refinements to SOC are of the essence.

In addition, it is not always easy to differentiate SOC from very different explanations of the occurrence of 1/f law. Consider the example of the size distribution of firms that was introduced in our earlier discussion of emergent properties of complex systems. A variety of explanations have been offered to explain this distribution, but none has been unanimously accepted (Sutton, 1997).

To explain the ubiquity of the 1/f law, Simon (1955) demonstrated that 1/f distributions correspond to the stationary state of stochastic processes where the probability that an event occurs is proportional to the number of times it has occurred in the past.[3] This interpretation provides a semantic argument, which is basically Gibrat's law of proportional effects (Gibrat 1931). This is used to justify the relevance of 1/f distribution in a large variety of cases like the Zipf's law in linguistic (Zipf 1949), the distribution of the number of publications among scientists, the distribution of wealth in some societies, or the distribution of the sizes of large cities. The problem with this interpretation is that it implies that to explain the size distribution of firms, the rate of growth of a firm would have to be proportional to its size. However, this is not what is observed. In fact, the relative rate of growth of firms seems to decrease with their size (Sutton 1997).

1/f distributions may have a still completely different origin. They may reflect the tail of a stable non-Gaussian distribution (Samorodnitsky and Taqqu 1994), which is known to have an asymptotic power law behavior (Mandelbrot 1963). This would mean that the distribution of sizes of business firms is the sum over a large number of independently identically distributed random events, with large variance (Gnedenko and Kolmogorov 1954).

The fact that the 1/f law is one of the most fundamental and conspicuous features of complex systems raises the interesting possibility that the ultimate explanation for the size distribution of firms may reside in CST. If the size distribution of firms is due to SOC, it raises an important question: what are the underlying dynamics responsible for this distribution? It may be related to the dynamics of growth of business organizations in a competitive economy. Or it may reflect a dynamic equilibrium of some sort or even a dynamic optimum.

It is likely that 1/f laws may occur in other areas of OT as well. The SOC paradigm may be potentially useful in prompting organizational researchers to pay increased attention to identifying underlying distributions. It may also provide dynamic explanations as an alternative to traditional stochastic explanations.

Self-Organization. Self-organization is a dynamic process by which under its own dynamics, a system spontaneously gets increasingly more organized. Biological evolution can be construed as the ultimate form of self-organization, i.e. a dynamic process leading systematically to increasing levels of organization and complexity. Self-organization in biological evolution seems to be an accelerating process. Most of biological evolution took place in the last 15% of earth's history (Leakey & Lewin, 1995). Self-organization is a feature of any group of individuals and organizations (Thompson, 1967). Self-organization supposes an increase of information. This means that the system does not evolve towards its maximum of entropy, i.e. an important part of its dynamics takes place out of equilibrium (Nicolis & Prigogine, 1977).

Systems that consist of a large number of interacting elements can display self-organizing behavior. Using a

Boolean cellular automata, Kaufmann (1993) found indications of self-organization in systems of interacting sites. These are systems where the state of a site is affected by the state of its neighbor(s). Self-organization in such systems means, that over time, the different sites build spontaneously nontrivial, organized configurations of states. In such systems, the level of connectivity (i.e. the number of sites with which a given site interacts) is a crucial parameter (Derrida & Weisbuch 1986a; Derrida & Stauffer, 1986b). When the connectivity is very low (each site interacts with only one or two other sites), these systems do not tend to display any interesting behavior. But when the connectivity is allowed to increase, these systems can display self-organizing behavior before becoming chaotic ("Life is at the edge of chaos" (Langton 1990)).

No good characterization of self-organizing systems exists yet. The few known ones tend to evolve slowly and go through metastable states (Paczuski et al. 1995). They do not display the systematic tendency toward increasing and accelerating self-organization which characterizes the biological world.

One major source of interest for CST is the prospect that it could be a stepping stone to understanding self-organization. The difficulty in conceptualizing biological evolution within the context of classical physics is an old and well-known problem. The dynamics of life seems to deviate systematically from the second principle of thermodynamics. This is explained by pointing out that living matter violates some key ingredients needed to derive that principle: it is an open system out of equilibrium. That life is not precluded by the second principle of thermodynamics is not enough. What is still missing are examples of dynamic systems which self-organize in a way similar to what happens in life. The fact that some systems studied under the aegis of CST seem to have elements of self-organization suggests that CST may eventually provide the key to this tantalizing question. Hence self-organization is a major preoccupation in CST. This has great significance to OT as this problem is consistent with the view of organizations as self-evolving systems that are neg-entropic (Katz and Kahn 1966).

Applying CST to OT—Some Illustrations

The foregoing discussion was aimed at providing an overview of CST. In this section, we turn to the task of demonstrating how CST concepts can be extended to the study of organizational phenomena. What follows is not a complete model of organizations based on CST. Such an exercise is beyond the scope of this paper. We attempt the more modest task of approaching some important areas of organizational research from a CST viewpoint. Our intention is to provide concrete examples to show how CST can inform and enhance OT.

CST approaches are best suited to the study of phenomena that are dynamic and nonlinear, and that exhibit emergent properties such as self-organization. In addition, CST is only useful when the phenomenon can be represented mathematically and/or computationally. Based on these criteria we chose two areas of research in OT to illustrate the application of CST—organization evolution and social network analysis.

Ecological research on organizational adaptation and selection study the effect of the environment on organizational mortality (Baum and Oliver 1991), rates and effects of change (Miner et al. 1990), and performance (Barnett and Carroll 1995). The central question in this area is the evolution of a population of organizations. The research designs and analytical techniques used in these studies, with a few recent exceptions (Bruderer and Singh 1996, Lomi and Larsen 1996), rely primarily on the collection and analysis of empirical data. This is an area where the use of CST-based computer simulations can provide fresh insights.

Another influential approach to the study of organizations is social network analysis. This approach to structural analysis views social structures as composed of networks of people who are linked to one another by different types of ties (White 1970). An example of a "network tie" in an organization would be people who work with one another. Network perspectives view organizations as networks of individuals, industries as a networks of organizations, and so on. In recent years social network analysis has emerged as an important perspective for studying organizations. It has acquired several theoretical and methodological tools from graph theory (Krackhardt 1994, Wasserman and Faust 1994). The etiology and dynamics of networks continues to be a central research concern in social network analysis (Nohria and Eccles 1992). Questions about how networks are formed and how they continue to evolve and change over time are fundamental to this area of research (Dorian and Stokman 1997). Here again, CST approaches may provide fresh insights.

Organizational evolution and social network analysis are also compelling because of the hint of self-organization underlying both areas of inquiry. This is very attractive from the perspective of CST, in which self-organization is a central preoccupation. Our discussion of self-organization is designed to convey the ambiguous beauty of this fascinating but also frustrating area in complexity theory. A few spectacular results have generated a lot of speculative papers. There are still major holes and limitations in our present understanding of self-organization which tends to be concealed by a veil of confusion. We spend some time emphasizing the difference between what has been observed mathematically, which we refer to as "dynamic self-organization," and what some want to see in it, i.e., the seeds of an explanation for biological evolution. The latter poses a much more formidable challenge. We use the detour of random graph theory to characterize this challenge. Random graph theory allows us to discuss how the self-organization relevant for OT still differs from "biological self-organization" and to connect it to the analysis of social networks.

Extending the principles and practices of CST to OT may imply increased use of computer simulations. However, it must be noted that, quite independent of CST, the use of computer simulation approaches has been gaining ground in organizational studies (see Carley 1995 for an overview; also Prietula et al. 1998). In fact, research based on simulation methodology such as Cohen, March, and Olsen's (1972) garbage can model and Nelson and Winter's (1982) evolutionary theory of economic change has had significant impact on OT. In recent years, computer simulations have been used to study organizational learning (Levinthal and March 1987, Lant and Mezias 1990, Carley 1992), organizational adaptation and selection (Levinthal 1997), and organizational evolution (Lomi and Larsen 1996). What lends a distinctive character to CST-based computer simulations is the role of paradigms such as SOC and self-organization in the development and analysis of models.

Evolutionary Models of Organizations

The emergence of population ecology theory in OT has given rise to number of ecological models of organizational change. Organizational changes affect the anatomy and physiology of organizations (Powell and DiMaggio 1991). The forces of organizational changes have internal components and external components (Hannan and Freeman 1989). In principle, the purpose of organizational change is to improve the performance of an organization (Amburgey and Rao 1996). In practice, and this is one problem with setting up an adequate evolutionary model for organizations, the logic of organizational change cannot be reduced to maximizing a well-defined fitness function.

Simon (1964) points out that it is doubtful whether decisions in organizations are directed toward achieving a goal. It is easier and clearer to view decisions as being concerned with discovering courses of action that satisfy a whole set of constraints. According to Simon it is this set that is most accurately viewed as the goal of the action. Hannan and Freeman (1989) go even further and argue that organizational change is largely uncontrolled and the consequences of designed structural changes are difficult to anticipate. By combining these viewpoints, we can conclude the following:

PROPOSITION 1. *The evolutionary dynamics underlying organizational changes is a mix of randomness and reaction to external and internal pressures. Although it is not driven by "fitness," it is successful only if it leads to an increase of fitness.*

In this section we discuss a class of evolutionary models inspired by the OT literature (Bruderer and Singh 1996), but directly abstracted from the CST literature (Bak and Sneppen 1993), which captures the essence of the previous remarks. In CST language the organizational structure is an emergent property resulting from the interactions of many adaptive agents (Cohen 1984).

We represent organization forms as a set of "routines" (R_i $i = 1, N$) in the sense of Nelson and Winter (1982).[4] The same model would be possible (and in fact may be easier to test against data) if organizations were described as a set of interacting "units." To each unit/routine is attached a number ρ_i between zero and one which measures its performance level.

Assuming that the ecology of organizations shares a lot of similarities with biological ecology, we use an extension of the rules introduced by Bak and Sneppen (1993) to study biological evolution from a CST standpoint. The model of Bak and Sneppen is the simplest evolutionary model existing today with dynamic content that is rich enough to include features such as punctuated equilibria, dynamic self-organization, and 1/f power spectrum.

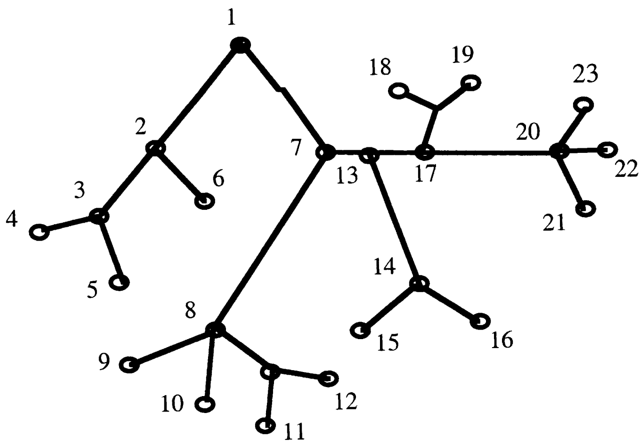
In the class of models we propose, organizational forms are characterized by a tree diagram (Figure 1) where the vertices represent the "units/routines," and the edges the connections between them. To each unit/routine (in Figure 1) is attached a number between zero and one which measures its performance level. (These nodes can also be seen as people where the links between people can be "works with" ties). The performance levels are drawn randomly.

Two kinds of changes may occur: changes which affect the performance of some units/routines without affecting the overall structure of the tree; and changes affecting the shape of the tree (modifying the connection structure, deleting some, or adding new units/routines). In this paper, we consider only changes that affect performance without affecting the topology of the tree.

Several rules of evolution are possible. We choose a rule that has the advantage of being simple and natural:

Figure 1 Example of an Organization Form

The shape reflects the structure of the organization. Here it has been chosen arbitrarily.



i) identify the node which has the lowest performance level, and ii) draw a new random value for the performance of that unit/routine, as well as for all the routines which are directly connected to it. In the organizational context, such rules are typically implemented by initiating changes in, or shutting down, the worst performing units. This assumes that a change in a unit/routine affects the performance of the units/routines connected to it. This procedure is iterated again and again. This model incorporates a rule of evolution that is different from those used in population ecology (Bruderer and Singh 1996). This suggests the following:

PROPOSITION 2. *It is possible to define evolutionary rules of changes of organizational forms which are not directly elicited from the fitness functions.*

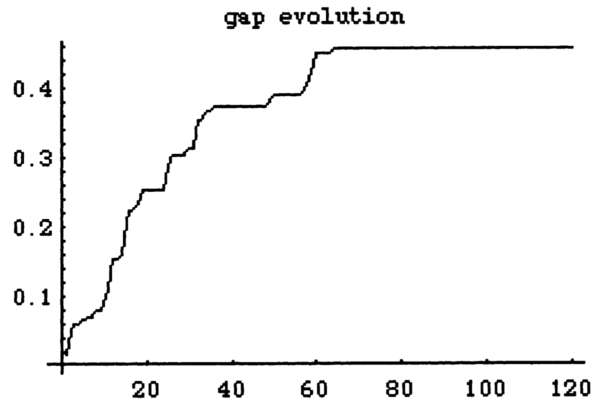
More generally, this approach acknowledges that maximizing a fitness function is not a necessary feature of models of evolution. This means that organizations can evolve although they are not trying to maximize their fitness function. This approach permits us to investigate the evolution of organizational forms by using a realistic set of rules that are consistent with the boundedly rational property of organizational systems.

An interesting quantity in this model is what Bak and Sneppen call the "gap," but which we will refer to as "reference performance level" (RPL). RPL is the largest value of performance that the lowest performing unit/routine had in the history of the organizational form (see Figure 2).

The value of this quantity at the beginning is the value of the overall minimum. If the new minimum is higher, it takes that new value; otherwise it stays at its original

Figure 2 The Gap (Reference Performance Level) Climbs a "Devil's Staircase"

This is seen as an evidence of the fractal nature of the space in which the gap lives.

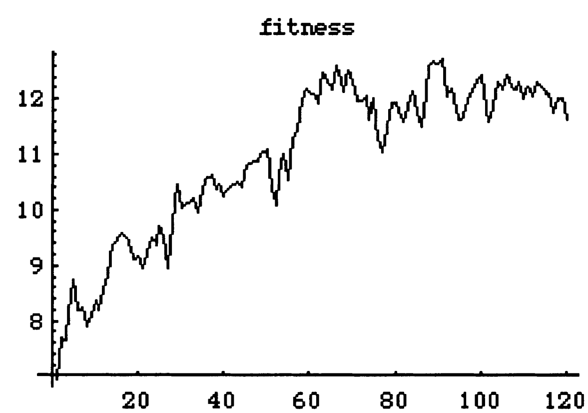


value. By definition, RPL can only increase. It represents a kind of reference threshold for low performance. The higher the RPL, the higher the lowest performance has been in the organization. An increase in RPL measures an increasing ability of the organization to maintain a high minimum performance. This turns out to be possible up to the point where the RPL becomes stationary (see Figure 3).

As we can see from Figures 2 and 3 (showing the evolution of the overall fitness of the firm), the evolution is divided in two phases. In one phase RPL increases, and in the other phase it is stationary. The variation in fitness across these phases is interesting. In the first phase the fitness increases. In the second phase the fitness oscillates but also ceases to increase (Figure 3). This is evidenced

Figure 3 Corresponding Evolution for the Fitness Function

Here the fitness function is an arbitrary linear combination (with weights) of the performances of individual unit/routines.



although the evolutionary rule of change was not elicited directly from the fitness function. This leads to the following:

PROPOSITION 3. *Fitness can benefit from changes even if the rules of evolution are not designed as an optimization algorithm for the fitness function.*

The idea here is that the organization needs rules by which to change or evolve over time. The application of these rules may but need not lead to an improvement in performance. These rules do not need to be consciously designed around a fitness function to lead to organizational performance improvement. Thus, while evolution may lead to increased overall fitness, it does not do so because of intent. OT has generally tended to assume that only successful firms evolve (see Levinthal and March 1987, March 1996, Carley and Lee 1998 for exceptions). What CST implies is that all firms evolve, but not all evolutions lead to successful adaptations. This may hold some interest for organizational theorists. It suggests that the system as a whole may and does exhibit properties different from those of its constituent elements. An organizational system can exhibit rationality at the systemic level that may run contrary to what a simple aggregation of the behaviors of its boundedly rational units may suggest. Models similar to the ones we have proposed may provide hints about the dynamics underlying some tantalizing organizational puzzles—how are organizations often more reliable than their composition of bias-prone individuals may suggest? Why do gains in individual productivity levels following the introduction of information technology not manifest themselves as gains in productivity at the organizational level?

The level of stationarity of RPL is related to the architecture of the tree and is a measure of the maximum level of performance that this kind of organization form can achieve. To increase it further, alternative measures have to be taken, like changing the shape of the tree. The dynamics of the evolution of the RPL may seem innocent. But a closer analysis reveals that it climbs a "Devil's staircase", i.e., the space of its values is a Cantor set (a fractal). The growth of RPL, which corresponds to a phase of improvement of the performance of the organization, goes through punctuated equilibria, i.e., periods of apparent stagnation between periods of changes, in a manner reminiscent of biological evolution. If one calls an "avalanche" the succession of steps during which RPL does not change, the system becomes stationary when the avalanche becomes infinite. One can show that when the "reference performance level" is increasing, the size of the avalanches is roughly inversely proportional to their frequency, i.e., it is "1/f"[5] (Figure 4). This is a signature of SOC (Bak and Chen 1991) and suggests the following.

PROPOSITION 4. *The dynamics of evolution of the "reference performance level" is self-organized critical.*

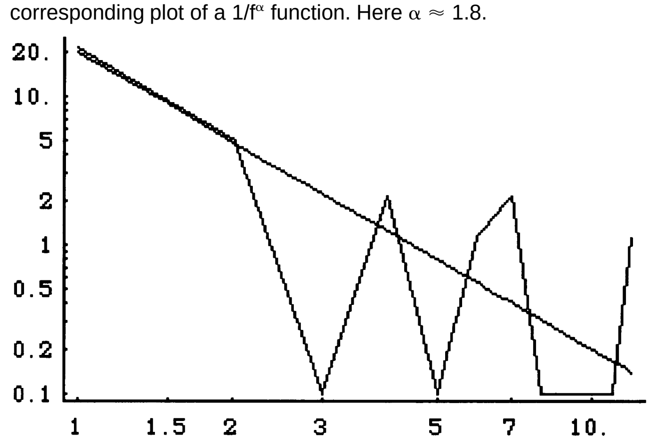
In the organizational context, this means that for a given configuration of organizational units and interconnections between them, there is a limit to growth in the reference performance level. When dynamic equilibrium is reached, the performance of the worst performing unit cannot be improved any further. Once this point is reached, performance can be improved only by changing the configuration by way of number of units or the interconnections between them. Dynamic equilibrium might help us examine the differences between emergent change and planned change.

To identify dynamic equilibrium, organizational researchers should attend carefully to the underlying patterns and distributions in organizational phenomena. For example, if the distribution of any feature of an organizational system, such as performance of units in an organization, follows the 1/f law, it may suggest that some adaptive process worthy of investigation is at play. Of course, our earlier caveat that we need to consider alternative explanations for the 1/f law must be borne in mind.

Figure 4 shows the distribution of the size of the avalanches of the changes when they are plotted against their frequency in a log-log plot for a single run of the simulation. As we can observe, there are large fluctuations around the 1/f behavior. Multiple runs would average out the fluctuations and result in a cleaner 1/f distribution. This illustrates another important feature of SOC in that kind of system: it is a statistical property. The fluctuations

Figure 4 1/f Distribution

Note: The size of the avalanches of the changes are plotted with respect to their frequency in a log-log plot and superposed with a corresponding plot of a $1/f^{\alpha}$ function. Here $\alpha \approx 1.8$.



of the 1/f distributions reflect the stochastic character of the processes involved. As noted earlier in this paper, the relationship between 1/f and stochasticity is quite promiscuous and complicates the interpretation of the emergence of 1/f laws.

The assumptions underlying the evolutionary model we used in this paper can be modified. It certainly would change the details of the outcomes. But some fundamental results are robust. The rules of evolution do not try to maximize the fitness function. They merely reflect the desire to improve the perceived lowest level of performance within the organization.

We conclude this section with an observation and some speculations. The main observation is that it is possible to have evolutionary models of organization which are not optimization algorithms of a fitness function. Our first speculation is that the dynamics of the reference performance level may better reflect how an organization measures its own performance than an abstract fitness function. From an information processing viewpoint, it is more realistic for organizations to focus on the specific goal of improving the performance of their worst-performing units than on the more diffuse objective of maximizing performance. Second, the adaptability of an organization is probably related to the dynamics of the changes in performance. When there is change in the performance of a unit, it affects the performance of all the other units in the system. While this has not been captured in the model, it does require the organization to exhibit adaptability to such changes. Maximum adaptability of the organization may correspond to a situation when those changes build a self-organized critical system.

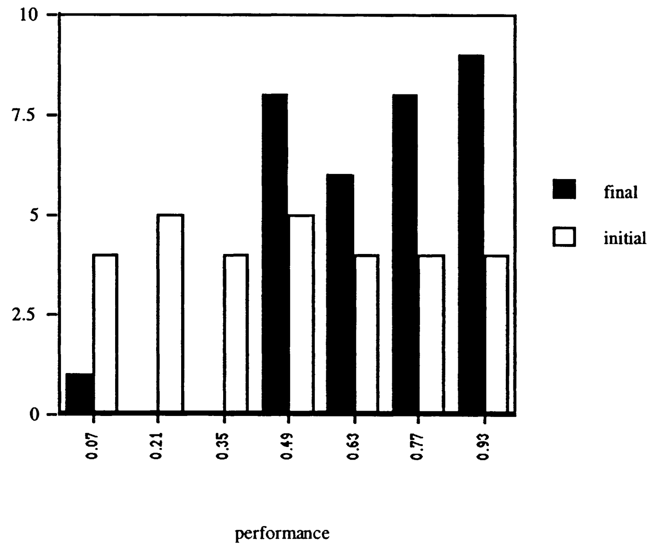
Clearly organizations have to make their ways between two extremes: too few or too frequent large changes. There must be an optimum mix of large and small changes which maximizes the adaptability of organizations and may be related to the emergence of SOC. An organizational example here is what is the right or optimal rate of executive turnover or restructuring. If the analogy with the heartbeat is at all relevant, it suggests that this optimum mix, i.e. the mix which maximizes the adaptability of the organization, could correspond to a 1/f distribution of the magnitude of organizational changes. This is a pure speculation. But it can be tested against empirical data.

Self-Organization

The evolutionary model discussed in the previous section has another dynamic property of interest to CST. It also displays what we will call "dynamic" self-organization, as opposed to other forms of self-organization that we discuss later. Figure 5 shows the performance distribution initially and when the steady state begins.

Figure 5 **Performance Distribution Initially and When the Steady State Begins**

Note: Although there are large statistical fluctuations (the number of routines is not very large), clearly the distribution of performances shifts to higher values. This is evidence for dynamical self-organization.



After RPL stabilizes, i.e., when the dynamics of organizational changes becomes stationary, the evolutionary model ceases to be self-organized critical. It is then "dynamically" self-organized. In this class of models, SOC is a feature of the dynamics of change leading to a self-organized state. Dynamic self-organization corresponds to the spontaneous emergence of skewed distributions for the performance levels. Self-organization in those systems is a statistical statement. It takes place in a reproducible way with high probability, after many iterations. It appears slowly, after the system has gone through several metastable states (punctuated equilibria). The evolutionary model described above displays "dynamic self-organization".

This kind of dynamic self-organization was originally observed in a certain class of cellular automata[6] and has been a source of rather intense mathematical interest (Derrida and Stauffer 1986b). It provides an example of dynamics leading to a decrease of entropy in some systems (Wolfram 1984, 1983). However, the source of this dynamics is unclear. Detailed studies of dynamic self-organization reveal intriguing features. Its occurrence depends on the degree of connectivity, i.e., the number of sites with which one site interacts (Derrida and Stauffer 1986b).

Neither the self-organization seen in biology nor the self-organization relevant for OT can be reduced to the shape of the distribution of values of state variables evolving separately. Life may have started slowly as in dynamic self-organization. The first eucaryotic cells appeared only 1.8 billion years ago. But there has been a spectacular acceleration in the pace of evolution, as if it were an important feature of the process. Most of biological evolution took place in the last 15% of current earth history, since the Cambrian explosion 530 million years ago, when the first complex multicellular organisms appeared (Leakey and Lewin 1995). This suggests the following:

PROPOSITION 5. *Dynamic self-organization does not have the potential to explain the systematic tendency of life towards increasing complexity at an accelerating pace.*

To explain the increased complexity and accelerating pace, we need to consider "biological self-organization." It was Kauffmann (1993) who pointed out the possible relevance of a theorem from random graph theory to the explanation of the origin of life. In this theorem, Erdös and Rényi (Cohen, 1988) addressed the very academic question of what happens to random graphs if the number of vertices and the number of edges N grow at a different pace. What they have actually established is the existence of "threshold functions." The relation between this theorem and biology is not immediately obvious. Yet it turns out that this theorem projects a very suggestive light on the different forms of self-organization, on the origin of life, and on what could be the origin of the acceleration of the process and its tendency to lead to increasingly complicated structures.

Consider a graph. It is made of vertices and the edges joining them. If all the n vertices of a graph involving N edges are joined to each other by one edge, there are exactly $N = \binom{n}{2} = n(n - 1)/2$ edges and the graph is called "complete." Concretely, the theorem shows that if the number of edges, N grows like or faster than $n^{k-2/k-1}$ ($N\, n^{(k-2)/k-1}$), the probability of finding trees of order k[7] is asymptotically (i.e., when $n \rightarrow \infty$) equal to 1[8]. If $n\, n^{2(k-2)/k-1}$ asymptotically, the probability of finding a complete subgraph of order $k \geq 3$ is 1.

Although it may look fastidiously technical, this result has far reaching implications.[9] It can be used to try to understand how life started. It implies the possibility of a phase transition in polymer biochemistry that could be the first step towards the creation of living matter. Polymers are the basic ingredient of life. When the number of different polymers in a solution[10] becomes large enough, the probability P that at least one of them can catalyze the synthesis of another one becomes significant and asymptotically equal to one.[11] In other words, there is then "catalytic closure," through the sheer effect of large numbers and interactivity. This was presumably the prelude to the manufacture of larger and larger molecules which eventually make living matter. This suggests that large numbers play a fundamental role in life.

PROPOSITION 6. *The mere occurrence of large numbers of nodes in random graphs generates conditions for self-organization which do not exist for small numbers.*

While the effect of large numbers is relevant for self-organization in biology, we need to be careful about interpreting its implications for self-organization in organizations.

It is not at all clear what "large" means in the context of social units. The large numbers discussed in physics and biology are typically in the order of millions. In most social contexts, such large numbers are difficult to conceive. The Internet has created a new situation where millions of people can interact. The spontaneous emergence of Internet communities could follow a dynamics along the lines similar to biological self-organization. In most organizations however, a size of a few thousands would be considered large. Will the implications of large numbers make sense in such a context? One reason that large numbers work in physics and biology is that they lead to complex ties which in turn lead to self-organization. However, in human beings the ties are already complex (Wellman 1988). People typically have multiple roles, and this introduces complexity in their interactions with people. In the vocabulary of social networks, human ties are "multiplex." This may mean that the notion of what is "large" and sufficient for self-organization in organizations may have to scaled down to acknowledge the inherent complexity of such ties. In our current state of knowledge, we are very far from being able to know whether this is indeed true.

The self-organization in organizations does not require a large number of agents. Organizations are made of human beings, i.e., very complicated functional units with very complicated interactions. One way to think about these units is in terms of subgraphs. In random graph theory, self-organization is associated with the spontaneous emergence of connected subgraphs. A connected subgraph describes a functional relation between several constituents. It can be construed as a functional unit not disconnected from other units. Examples in organizations would be cliques and departments.

The more complicated the functional units are, the more varied and complex the external connections they can have. The reasoning of Erdös and Rényi could be extended to exotic graphs we will call "hypergraphs," where the vertices are functional units (i.e., aggregations of subgraphs) that can have many kinds of interactions simultaneously. The probability of finding complete subgraphs of some sort in hypergraphs is very large, even with a limited number of functional units. Functional units of higher complexity and variety can be created by building increasingly complex structures. At this stage, this is pure speculation. But it is also a powerful framework to conceptualize self-organization.

Connected graphs build functional units whose interactions are more complex than those of individual vertices. These functional units may be the building blocks of organizational structure. This suggests that self-organization leads to multinode conglomerations, which is similar to the institutionalist notion of network structuration (Powell and DiMaggio 1991). Random graphs provide a space in which the dynamics of self-organization takes place. The self-organizing dynamics has still to be developed. A couple of decades ago, a "dissipative self-organization paradigm" (Nicolis and Prigogine 1977) was developed. The fundamental ingredient of that approach is the observation that self-organization as a dynamic process can take place only out of equilibrium. When it was tentatively applied to OT, one major finding was that this paradigm may be useful to understand situations of turbulence when self-organization leads to quieting (Smith and Comer 1994). The turbulence created the conditions for the group dynamics to get out of its original equilibrium and to find a new one as a different, quieter functional unit.

A self-organization materializing in an increasingly complicated organizational architecture is not easily reproducible with a paradigm based on dissipation only. The dynamics out of equilibrium has to materialize into increasing complexity. It is as if the new functional units can be reached only through large perturbations that push the system out of equilibrium. And once created, the functional units tend to be robust. The concept of "functional units" bears some similarities with the concept of adaptive agents (Holland 1995).

PROPOSITION 7. *Connectivity is an important parameter for dynamic self-organization. The interaction between complicated functional units may result in self-organization of increasing complexity.*

We can think of the graph as having several planes where the nodes are in one plane and the functional units resulting from the connections between the nodes are at a higher plane. In this case, the increased complexity will be observed in the interconnections among nodes as well as functional units. If this is true, and can be extended to organizations, it anticipates and predicts an important and empirically observed trend: the emergence of structurally complex "network organizations" which are neither markets nor hierarchies (Powell 1990, Eccles and Crane 1987).

This discussion of self-organization illustrates the complexity and fertility of the interface between CST and OT. What is referred to as self-organization in CST is a slow and statistical dynamic process that bears little in common with what is seen in biology and OT. Random graph theory is a powerful framework to discuss some fundamental features of biological self-organization. Admittedly, the relation between random graph theory (as discussed in this paper) and OT is tenuous and raises more question than it answers. Random graph theory could play a more important role in CST, as it does in the study of social networks in OT. It could provide a useful common ground of research for both fields. At this stage of our understanding of self-organization in CST, its best use for OT may not be as an aid in the development of a mathematical model supporting some assumptions, but as a source for enriching the conceptualization of self-organization.

This exercise may also serve as a useful framework to generate interesting questions. For example, what happens to the dynamics of self-organization as the size of the graph (or network) grows? What happens to interorganizational relationships and organizational fields as size increases? What effect does the introduction of technology have on self-organization? One possibility is that the introduction of new technology may result in a faster increase in the rate of connections than in the number of agents. This may have very different implications for self-organization compared to a situation where technology leads to a reduction the number of connections (e.g., artificial agents). Although there are no simple answers to these questions, they do suggest the intriguing possibilities raised by combining insights from graph theory to the study of self-organization in networks.

Discussion

The preceding discussion raises a variety of methodological and epistemological questions. Given the absence of a commonly accepted formal structure for CST, researchers in OT must be cautious in borrowing pieces of CST. Application of CST to OT must rely on mathematically proven or computationally justified facts. Approaching OT from a CST standpoint is a way to use mathematical modeling in what is a human or social science. This is not new in and of itself. Whenever dynamics is involved, there is no good alternative to mathematical modeling. As Simon (1987) observed, mathematics is useful not only for quantitative analysis, "a common delusion," but also and more importantly to analyze situations too complex to be understood by words. Mathematical and computational models are irreplaceable to test dynamic assumptions, as words and concepts are not a good instrument to analyze dynamic processes. This was abundantly illustrated in physics, where one has just to compare the physics of Descartes and Aristotle with the physics of Galileo and Newton.

But the use of mathematical models carries its own epistemological complications. Researchers should be careful in extending catch phrases from CST to OT. First, the detours through mathematical modeling may introduce biases in the analysis towards overemphasizing the importance of dynamic processes in areas of their maximum applicability. Second, a mathematical model may or may not be valid. An example of an invalid mathematical model is one with too many parameters, which makes the model like a black box, and an act of faith is needed to believe in its "predictions." Another kind of invalid model involves uncontrolled or random assumptions. But unfortunately "validity" here is a bit like a sunset: the distinction between the red and the blue may not be easily identifiable. Approaching OT from a CST standpoint creates a mindset which may lead to biases. One may be tempted to plug in CST concepts or to solicit ambiguous facts.

An additional source of epistemological complication is the fact that the mathematics of CST are much less polished than other branches of mathematics, like dynamic system theory. The concepts used like SOC and self-organization clearly need refinements. The choice of CST models for use in OT can be based on misleading or altogether irrelevant analogies. For example, if out of a CA simulation of interactive agents, one recognizes an emergent property which bears some resemblance with something observed in human organizations, what is the message? The interaction between human beings is unavoidably far more complex than the interaction between the agents of the CA. To what possible extent can the outcome of a simplistic dynamics be construed as an "explanation" for a far more complicated situation? Is the word "allegoric" an adequate protection?

Still, CST can also be a very powerful instrument of analysis. It can help in identifying the minimum set of ingredients necessary to reproduce a robust observation. It can be a laboratory to (in)validate dynamic assumptions about the life of organizations and their interactions. It provides powerful tools to test concepts like self-similarity further than the anecdotal level. It may inspire new hypotheses as suggested by the example of the origin of adaptability. It may also lead to the development and use of new powerful analytical tools. One can imagine CA-based simulations which would allow us to discuss much more cogently the life of communities, organization, the emergence of hierarchies and their functions, etc.

The examples used in this paper were supposed to represent two different epistemological situations: SOC in the dynamics of organizational changes and/or underlying the size distribution of firms, expresses a mathematical regularity which is to a large extent measurable and which may reveal something important about the life of organizations and their interactions. This knowledge, which could not have been guessed without the detour of CST, could affect our understanding of the problem. If it can be shown that adaptability is related to the SOC nature of the changes in an organization, that could be an important contribution of CST to OT.

The discussion about self-organization illustrates a more complex epistemological situation. We did not do an extensive analysis of self-organization in OT. We merely pointed out that what CST has to offer is a far cry from what OT needs. But in the process we try to convey that CST has developed deep insights into what self-organization entails, even if it may not have yet the mathematics to back them fully. At this stage, taking a CST perspective with respect to self-organization provides a standpoint, a set of biases or potential insights, something closer to a state of mind than a rigorous methodology.

In conclusion, an important implication of this paper, albeit undiscussed, is that the CST concepts such as self-organization and SOC may be better understood by studying them in an organizational context. Just as OT can benefit from the CST emphasis on detecting and interpreting underlying patterns, CST can benefit from the OT emphasis on explicating and elaborating underlying processes. The bridge between the two fields goes both ways.

Acknowledgment

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Endnotes

[1]This distribution is observed only when the data is categorized such that the firms in the low end (firms under size 25) are lumped together.

[2]The game of life consists of a few agents distributed on a square grid (each site has eight neighboring sites). The rules are that when an agent is connected to fewer than two neighbors it dies of loneliness. If it is connected to three or more, it dies of being overcrowded. If three agents surround an empty spot, they give birth to a new one. Alternative rules can be invented.

[3]This is reminiscent of a Polya process, i.e., a stochastic process involving a positive reinforcement proportional to the value of the variable (Arthur 1995).

[4]They define routine as a "general term for all regular and predictable behavioral patterns of firms [. . .] to include characteristics of firms that

range from well specified technical routines for producing things, through procedures for hiring and firing, ordering new inventory, or stepping up production of items in high demand, to policies regarding investment, research and development or advertising and business strategies about product diversification and overseas investment" (p. 14).

[5]"1/f" actually means $1/f^{\alpha}$ where $\alpha \leq 2$.

[6]The so-called Boolean cellular automata are a special kind of dynamic systems: Boolean means that the state of the systems corresponds to a list of "one" and "zero." The list of ones and zeros is updated at time $t + 1$ from the knowledge of the state of the system at time t, through a predetermined set of rules.

[7]A tree of order k has k vertices joined together by $k - 1$ edges.

[8]If $k = 3$, the statement is that if the number of edges grows like the square root of the number of points ($N \propto n^{1/2}$, or $\lim_{n\to\infty} N/n^{1/2} = c$, where c is a *const* $\neq 0$), at the limit $n \to \infty$, the probability of finding a tree of order 3 in any graph $G_{n,N}$ is asymptotically finite.

[9]$n^{(k-2)/k-1}$ and $n^{2(k-2)/k-1}$ are the "threshold functions." A possible illuminating use of this result is to apply it to the physical states of matter: The solid phase corresponds to the case where the connectivity is larger than the threshold functions for trees of the size of the crystal, gas corresponds to the case where the connectivity is smaller than the threshold function for $k \geq 3$ trees ($N < n^{1/2}$), and the liquid corresponds to an intermediate situation. Another potential example (although one whose implications are unclear) is the observation that the brain has 10^{12} neurons and 10^{15} random connections or synapses. This implies that by the sheer law of large numbers, the brain contains naturally complete subgraphs of order $k > 3$.

[10]For a given length M, the number of different polymers is: $\approx 2^{M+1}$. N is the number of ways the polymers interconnect, i.e.: $N \approx \sum_{i=1}^{M-1} 2^{M-(i-1)}(M - i)$. The ratio of number of reactions by which polymers can interconnect to the number of kinds of polymers $N \approx M - 2$, i.e., it increases with the size of polymers faster than the threshold function of Erdös and Rényi.

[11]$P = 1 - (1 - p)^{(M-1)2^{(M+1)}} \approx 1 - e^{-p(M-1)2^{(M+1)}}$.

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