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Self-organization dynamics

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Abstract—In its unparalleled wisdom nature creates adaptively complex self-organizing systems (SOS), which produce the dynamic (i.e., through-time) behavior patterns that physicists and life scientists see. A system is an organized group of interacting components working together for a purpose. Control over the system's organization is either centralized in a distinct subsystem, or distributed among evenly contributing components. Distributed control enables self-organizing systems to create globally coherent behavior patterns (i.e., dynamics) spontaneously out of local component interactions.

Keywords: autopoiesis, simulation, strategy, system dynamics, virtual enterprise networks

Introduction

What links embryos and hurricanes, the pattern of stripes on a zebra and the rhythmic contraction of your heart, or persistent cycles in real estate markets and neural networks, is that they are all self-organizing systems: their dynamics arise spontaneously from their internal structure. Their feedback-loop structure amplifies small perturbations (variations), generating behavior patterns in space and time that create path dependence. SOS dynamics is typically non-linear because of the circular or feedback-loop relationships among system components. Positive feedback leads to explosive growth dynamics, which ends when all component behavior has been absorbed into a new configuration pattern (i.e., attractor), leaving the system in a stable, negative feedback state.

Intrigued by SOS ideas and processes, such as autocatalysis, autopoiesis, bifurcation, chaotic attractors and fractals, business researchers and practitioners eagerly adopt them. Evidently, SOS business applications fall into two unambiguous categories. The first is metaphorical and the second computational.

Challenged by today's accelerating economic, environmental, social and technological change, and by the growing complexity of the systems in which we live, managers borrow nearly arbitrarily fashionable scientific concepts. Philosophers, literary or art critics and mystics support metaphorical SOS connotations. Nobody can forbid metaphors, but simile and analogy alone describe SOS outcomes onlyneither why nor how their processes work, thereby treating self-organizing systems as if they were a black box.

Much more conducive to effective decision making through high-level learning, the second applications category entails multi-loop translations among SOS language, pictures and models (mathematical and simulation). Its purpose is to make the black box transparent; to understand why and exactly how SOS generate magnificent patterns; how SOS structure causes behavior.

The metaphorical SOS treatment with examples linking business to nature captures the imagination of business managers and scholars, but demands maintaining a tolerant yet skeptical view of its connotations. Benefiting from SOS requires preserving their rigor through simulation modeling. Modeling SOS also helps avoid either being unduly metaphorical (i.e., hand waving), or blindly trying to import theories from the physical and life sciences to our domain's craft. Indeed, the benefit from computing SOS dynamics is understanding contemporary business phenomena, such as the emerging virtual enterprise networks (VENs) with their autopoietic industry value chains.

The need for a new metaphor

The madhouse rate at which business is changing today no longer bears any resemblance to some managers' internal models of reality. Consequently, full of stress, uncertainty and anxiety, they do not know how to act. Founder and CEO emeritus of VISA, Dee Hock (1998) sees three ways in which managers might respond:

First, they can try to impose their perception of reality on external circumstances to make reality behave the way it shouldwhat many institutions try to do today. The second alternative is for managers to go into denial, refuse to think, insulate themselves from reality or create another reality they do understand. The third alternative requires that managers examine their internal models of reality and try to change them. This is difficult because it (a) questions one's whole identity and sense of value in the world, and (b) requires high-level learning. Yet, this is the only alternative that works.

The internal or mental model of almost everyone in the world today shows in the machine metaphors we utter: he's a big wheel, she went ballistic, he's got a screw loose, the group is ticking like a clock, we need to get in high gear, let's reengineer the organization, etc. All these are machine metaphors and analogies. But you would die if you reengineered your body according to them. Where would the CEO of the immune system and the brain be?

Business leaders have built for years on Newton's mechanics principles, as if people were gears in a timepiece. And it worked, until modern life's speed of change and complexity began to overwhelm grand hierarchies, from the Soviet Union to the mainframe computer. The new framework for business is the biological world, where efficient actions produce robust results through autopoietic adaptation (Zeleny 2000).

Nature helps discover alternatives to mechanical organization. Focusing on nature's underlying system structures or processes explains the dynamics in living systems. Examples of such systems are human learning and intelligence, organizational adaptation and development, and the historical evolution of business firms. SOS ideas help organizational change efforts, such as business process (re)design. Self-organization entails spontaneous system change, however, a constant evolution enabled by distributed control and triggered by internal variations. Consequently, for a firm to exist, adapt, survive and evolve, it must integrate its suppliers and customers, and collaborate with competitorsa huge chunk of its business environment.

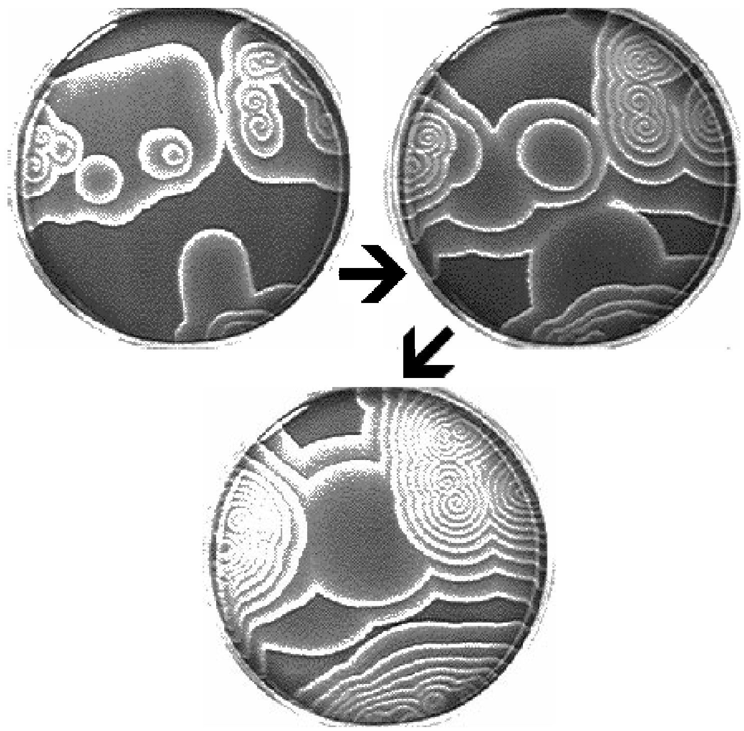
SOS: The new science

SOS have grown out of many disparate scientific fields, including physics, chemistry, biology, cybernetics, computer modeling, and economics. This has led to a quite fragmented approach, with many different concepts, terms and methods applied to seemingly different types of systems. A fundamental concepts and principles core has emerged, however, applicable to all self-organizing systems, from simple magnets and crystals to brains and societies. Salient SOS characteristics include: (a) bifurcations and symmetry breaking, (b) distributed control, (c) far from equilibrium dynamics, (d) global order from local interactions, (e) non-linearity and feedback, (f) organizational closure, hierarchy and emergence, and (g) robustness and resilience (Heylighen 1999).

Nature's spontaneous emergence of SOS dynamics is easy to see both in the laboratory and in our day-to-day world. A simple example is crystallization, the appearance of beautifully symmetric patterns of dense matter in solutions of randomly moving molecules. Other examples are certain chemical reactions, such as the Brusselator or the Belouzov-Zhabotinsky (BZ) reaction, where it suffices to pump ingredients into a solution in order to see dazzling, pulsating color spirals (Fig. 1).

Found by Belousov in 1958 and studied by Zhabotinsky (1973), the Belousov-Zhabotinsky (BZ) chemical reaction shows nature's SOS tendency as wave patterns in a Petri dish. The three progressive stages of Fig. 1 entail propagating oxidation waves in an unstirred layer of ferroin-malonic acid. Spiral waves develop when a gentle airflow through a pipette breaks the layer.

Figure 1 The Belousov-Zhabotinsky (BZ) reaction (Zhabotinsky 1973).



The oscillatory BZ reaction dynamics has implications not only for chemistry but also for biological systems. It contradicts the second law of thermodynamics, which says that the natural tendency of any system is to run down from a state of order to disorder, from enthalpy (energy) to entropy. Apparently, under certain conditions, homogeneous closed systems oscillate spontaneously around their expected stationary states when approaching equilibrium.

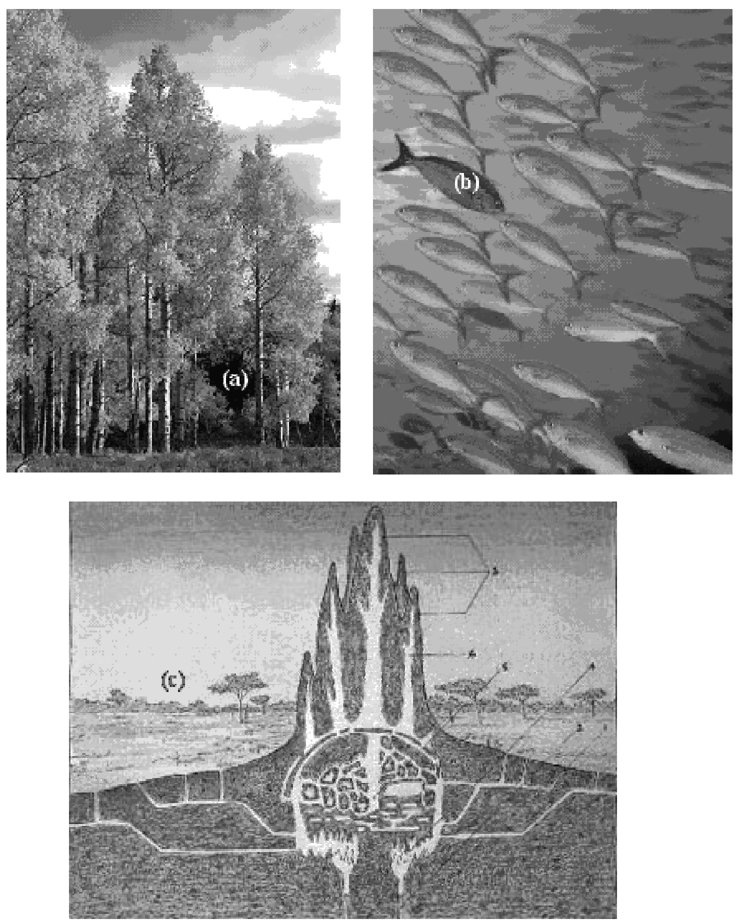
Reconciling SOS with thermodynamics is simple in the crystallization case. Molecules fixed within a crystalline structure pass on their energy to the liquid in which they were dissolved. An increase in the liquid's entropy compensates for the decrease in the crystal's entropy. The entropy of the whole system, liquid and crystal together effectively increases.

The solution is less obvious, however, when SOS do not reach equilibrium. Belgian thermodynamicist Ilya Prigogine received a Nobel Prize for his work on this problem. He and his colleagues at the Brussels school of thermodynamics have been studying dissipative structures (Prigogine & Strengers 1984).

Like the BZ reaction, dissipative structures show self-organization. Necessarily open systems, energy and/or matter flow through them. A system is continuously generating entropy that is actively dissipated, or exported, out of the system. Thus, it manages to increase its own organization at the expense of order in the environment. The system circumvents the second law of thermodynamics simply by getting rid of excess entropy. Living organisms show dissipative spontaneous dynamics. Plants and animals take in energy and matter in a low entropy form as light or food. They export it back in a high entropy form, as waste products. This allows them to reduce their internal entropy, thus counteracting the degradation implied by the second law.

Exporting entropy does not yet explain how or why self-organization takes place in non-linear systems, far from their thermodynamic equilibrium. Fortunately, autonomous systems in cybernetics complement the thermodynamicists' observations. Independently of its type or composition, an autonomous system always evolves toward a state of equilibrium (attractor). This reduces uncertainty about the system's state and, thereby, statistical entropy. System parts mutually adapt to the resulting equilibrium. Paradoxically, the larger the random perturbations (noise) that affect a system, the more quickly it will self-organize (produce order).

Figure 2 Aspen groves, shoals of fish and termite towers are magnificent SOS examples in nature (adapted from Wheatley, 1996; photographs by M. Jackson).



The idea is simple: the more widely a system moves through its state space, the faster it ends up in an attractor. No attractor is reached and no self-organization takes place if a system stays put. Generally, non-linear systems have several attractors. An attractor is either a stable equilibrium, i.e., a fixed point or a limit cycle, and thereby nonchaotic, or an unstable equilibrium, i.e., aperiodic or chaotic. When caught in between attractors, a system is in a chance variation, called fluctuation in thermodynamics, which pushes it into either one of its attractors (Prigogine & Strengers 1984).

Since the 1950s and 1960s, when SOS were first studied in thermodynamics and cybernetics, many examples and applications have been discovered. Prigogine generalized his observations to argue for a new scientific worldview. Instead of the Newtonian reduction to a static being framework, he sees the universe as an irreversible becoming, which endlessly generates novelty.

Cyberneticians apply self-organization to the mechanisms of mind, to understand how the brain constructs mental models without relying on outside instruction. A practical application is neural networks, simplified computer models of how the neurons in our brain interact. Unlike the central reasoning control used in artificial intelligence, there is distributed control in a neural network (NN). All neurons are connected directly or indirectly with each other, but none is in control. Yet, together they manage to make sense out of complex patterns of input.

Laser light is another SOS example. Atoms or molecules excited by an input of energy emit the surplus energy as photons, normally at random moments in random directions. The result is ordinary, diffused light. Under certain conditions, however, the molecules become synchronized, emitting the same photons at the same time in the same direction. The result is an exceptionally coherent, focused beam of light.

Plants and animals also provide examples of spontaneous collective behavior. An aspen grove in Utah, for example, is the largest known living organism on earth (Fig. 2a). Each tree is connected to all others by the same underground root systemone vast connection.

Flocks of birds, gangs of elk, herds of sheep, shoals of fish (Fig. 2b) and swarms of bees react in similar ways. When avoiding danger or changing course, they generally move together in an elegantly synchronized manner. Sometimes, the flock or shoal behaves as if it were a single animal. There is no head fish or bird leader, however, that tells others how to move. Computer simulations reproduce this behavior by letting individuals interact according to a few simple rules, such as keeping a minimum distance from others and following the average direction of neighbours' moves. A global coherent pattern emerges out of local interactions.

Similarly, the twenty-foot termite towers in the Australian savanna are the result of distributed control (Fig. 2c). Each termite colony is a magnificent example self-organization, producing intricate towers from the seemingly random movements of many individuals. Relative to the size of their builders, termite towers are the tallest structures on Earth (Wheatley 1996).

Metaphorical SOS applications

Nature helps managers willing to re-examine and to change their internal models of reality. As employees pursue their daily routines, changed managers encourage them to experiment, to make messes, to seek information and assistance in search of new ways to keep the company mission alive. Meanwhile, they create new streams of performance data so everyone can see what's working. In time, unpredictable new structures and flows take shape, success building on success. Whether because of financial or other stakes, employees display boundless new eagerness for the work they control. Instead of driving ambiguity and instability out, managers who adhere to nature embrace them both.

SOS principles won't succumb, however, to program-of-the-month syndrome because self-organizing adaptation is a ceaseless process in a real-time world of global business, with technologies, markets and relationships emerging and disappearing amid a fury of constant communication. And it recognizes the best of the baby-boomer culture and the detachment of Generation X. Naturally, some firms could be engulfed by the chaos they create but, so far, Petzinger (1997) sees nothing but success stories to report:

> In rural Virginia, for example, productivity soars at Rowe Furniture after workers take over production scheduling and problem-solving.
>
> At Koch Industries of Wichita, refinery operators who once turned dials according to carefully assigned procedures now come up with their own control techniques, causing huge gains in output. 'Complex human systems, whether societies or organizations, can only function properly by spontaneous order' says Charles Koch, who heads the $25-billion-a-year energy company.
>
> It's not some feel-good impulse driving executives in this direction: there's simply no faster way to react to change. Central planning is considered futile at Cardinal Environmental Inc. of Oklahoma City, which instead relies on its employees to act on ever-changing customer cues. 'We function like an amoebae that flows with the environment and constantly reshapes its body', says owner Steve Mason.
>
> On a larger scale, Monsanto is hatching a bold new R&D initiative from the self-coordinated effort of several employee teams. 'If an institution wants to be adaptive', Monsanto Chairman Robert Shapiro says, 'let go of some control, and trust people'.
>
> With self-organization seen both as a movement and good management, a diverse club of major outfitsCiticorp, Coca-Cola, Honda, Intel and the Veterans Hospital Administration among themhave become corporate affiliates of the Santa Fe Institute, the leading think tank on complex adaptive systems.
>
> A hot new magazine in Boston called <u>Fast Company</u> is riding the wave of bottom-up-leadership with distributed managerial control.
>
> 'Self-organization is all about de-engineering', says Ken Baskin, a former Bell Atlantic executive. Give employees the tools and the autonomy, he saysparticularly Americans, with all their education and independence'and they produce amazing results'. As a society we know the best way to organize people is freeing them to organize themselves. Why should it be any different in business?
>
> Are SOS the wave of the future, asks Petzinger (1997), or are we all washed up?

Since the 1980s, several well-articulated and well-received books in the business literature advocate the study of organizations from a self-organizing systems perspective. For example, Morgan (1993) argues that the metaphor of organizations as a self-organizing, self-producing system offers powerful conceptual tools to examine organizations in flux. Equally fascinated by SOS <u>connectedness</u> and <u>wholeness</u>, Senge et al. (1994) describe organizations as complex nonlinear systems, directed by charismatic leaders who intervene at critical leverage points.

Wheatley (1996) continues this advocacy about organizations as self-organizing systems by conveying the pleasure of sensing a new way of thinking about organizations. She acknowledges the danger in playing with science metaphors, but she also argues that all science is metaphor. Wheatley reduces SOS to mere images and uses their outcomes to define consciousness, thereby turning science back to anthropomorphic mythology.

These authors and their followers love to metaphorically re-conceptualize organizations as dynamic, chaotic, non-linear systems, with self-similar structures, given to sudden disruptive changes, often triggered by small, <u>seemingly</u> random actions. They offer illustrative anecdotes of organizational activities and structures that appear to bear out SOS characteristics. No matter how breathtaking, however, anecdotes hardly make up empirical evidence. Anecdotes and images are just metaphorical attempts to <u>imaginize</u> organizations (Morgan 1993).

The history of, and reaction to, earlier scientific metaphors suggest that disillusionment sets in when the public tires of the metaphor and the research community fails to see formalized intellectual advances. This time around, simulation modeling holds out the promise that disillusionment can be pre-empted, or at least delayed (Turner 1997).

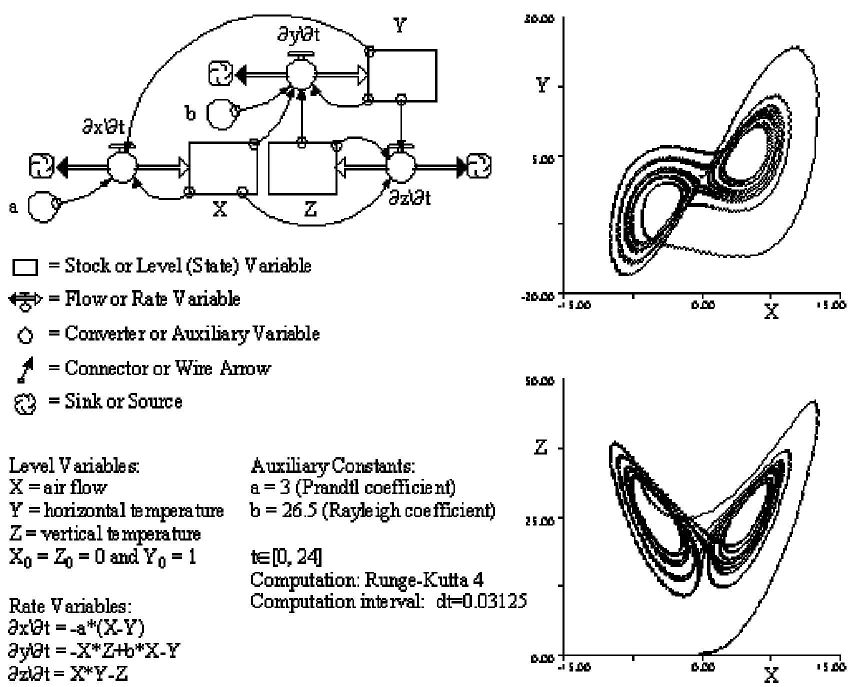
Computational SOS applications

Complexity theory and the exponential increase in computational power make simulation modeling a critical fifth tool in addition to the four tools used in science: observation, logical/mathematical analysis, hypothesis testing and experiment (Turner 1997). Simulation modeling permits researchers and practitioners in a variety of disciplines to examine the aggregate, dynamic and emergent implications of multiple nonlinear generative mechanisms.

Swarms are but one of the many self-organizing systems studied through simulation modeling. Inexpensive and powerful computers make it possible to model and explore highly complex systems. Simulation modeling helps the Santa Fe Institute researchers in New Mexico study complex adaptive systems, consisting of many interacting components, which undergo constant change, both autonomously and in interaction with their environment.

Typical examples are ecosystems, where different species compete or cooperate while interacting in their shared environment. By generalizing the mechanisms through which biological organisms adapt, Holland (1997) founded the theory of genetic algorithms. This approach to computer problem solving relies on the mutation and recombination of partial solutions, and the selective reproduction of the most fit new combinations. By letting units that undergo variation and selection interact through signals or resources, Holland extended simulation modeling to cognitive, ecological and economic systems.

Figure 3 These ordinary differential equations (rate variables) by Lorenz (1963) produce the butterfly-like attractor (XZ phase plot) that has become the symbol of chaos theory (e.g., Ormerod's 1999 book Butterfly Economics). Model diagram, equations and graphs created with iThink Analyst 6 (Richmond et al. 2000).



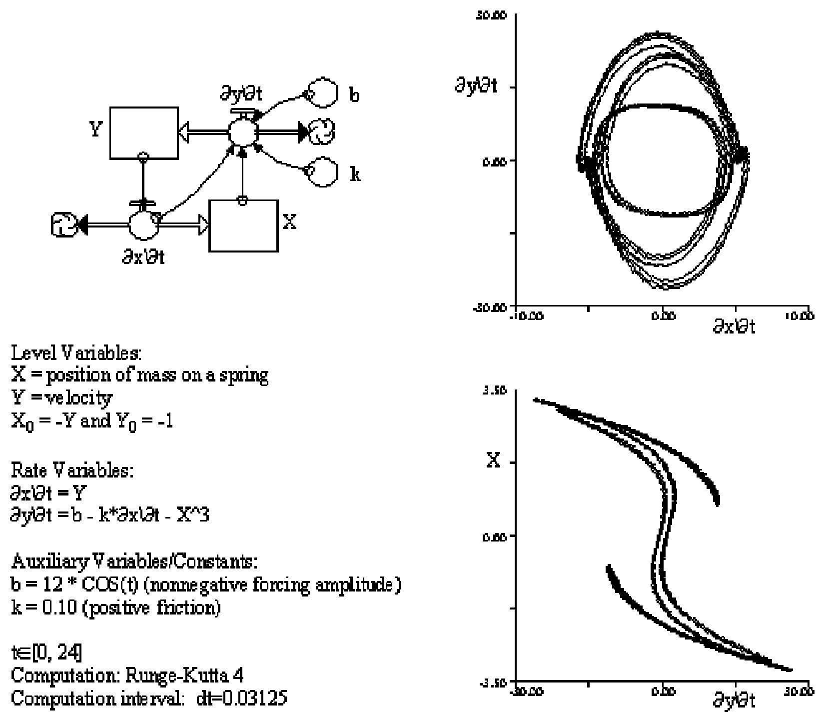
Markets are good SOS examples, where producers compete and exchange money and goods with consumers. Although markets are highly chaotic, nonlinear systems, they usually reach equilibria, attractors that satisfy changing and conflicting customer demands. The failure of communism shows that markets' distributed control is more effective at organizing the economy than a centrally controlled system. SOS computer simulations corroborate what Adam Smith, the father of economics, called the invisible hand (Sterman 2000, pp. 169-177).

Biologist Stuart Kauffman (1995) also studies the development of organisms and ecosystems. His simulation models show how networks of mutually activating or inhibiting genes differentiate organs and tissues during embryological development. Complex networks of chemical reactions self-organize into autocatalytic cycles, the precursors of life. SOS develop autonomously, and natural selection helps them adapt to variable environments.

Holland's and Kauffman's work provides essential inspiration for the new discipline of artificial life. This approach, initiated by Chris Langton, successfully builds computer programs that mimic lifelike properties, such as reproduction, sexuality, swarming, co-evolution and arms races between predator and prey.

Simulation modeling is also the chief catalyst for chaos theory. Using a deterministic simulation model of a weather system, MIT meteorologist Edward Lorenz (1963) discovered that even the most minuscule of changes cause drastic alterations in weather (Fig. 3). That effect defied both intuition and what meteorologists had previously understood about their science.

Figure 4 The chaotic attractor Ueda (1992) found in Duffing's system. Model diagram, equations and graphs created with iThink Analyst 6 (Richmond et al. 2000).



Intrigued by Lorenz's puzzle, scientists from different fields began experimenting with simulation models, only to discover similar dynamics. Yoshisuke Ueda (1992), for example, found a strange attractor in Duffing's system (Fig .4). The fundamental insight that minute changes can lead to large deviations in the behavior of a natural system has inaugurated a radical shift in how scientists see the world. For all practical purposes, the dynamics of even relatively simple systems is unpredictable. This is the butterfly effect (Fig. 4).

This does not mean that chaotic systems do not exhibit any patterns. While the idea of unpredictability is counterintuitive, chaos theory's second basic insight is even more so: behavior patterns do lurk beneath the seemingly random behavior of systems. Chaotic systems do not end up just anywhere. Certain paths show distributed intelligence or control (Fig. 3 & 4).

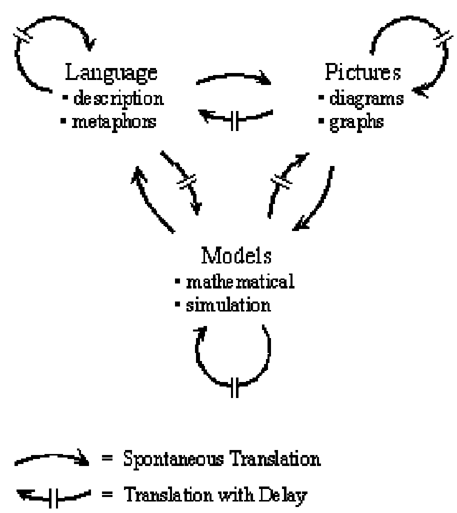
Like biologists who are simulating cells that arrange themselves into immune systems, economists are simulating the limited actions of individual buyers and sellers that form complex markets, industries and economies. Jay W. Forrester (1958) was the first to apply the computational principles of cybernetics to industrial systems.

Forrester's initial work in industrial systems has been subsequently broadened to include other social and economic systems and is now known as the field of system dynamics (Sterman 2000). Relying on the computer, system dynamics provides a coherent method for solving business, economic and social problems, particularly when chaotic attractors are involved (see for example the work of Erik Mosekilde and other system dynamics colleagues in the System Dynamics Review: Special Issue on Chaos, Richardson & Andersen 1988). A prerequisite for systems thinking, system dynamics simulation is the basis of this essay's SOS modeling example, which follows the overview of a high-level learning process framework, applicable to virtually all business situations.

High-level learning in and about SOS

Effective decision making and learning in a world of growing dynamic complexity requires managers to become system thinkers. To synchronize their mental models with today's business reality, they must use high-level learning (Fig. 5), which preserves SOS rigor and helps discern contemporary business phenomena, such as the emerging self-organizing business networks with autopoietic industry value chains (Zeleny 1999).

Figure 5 High-level learning: Multi-loop translations among language, pictures and models.



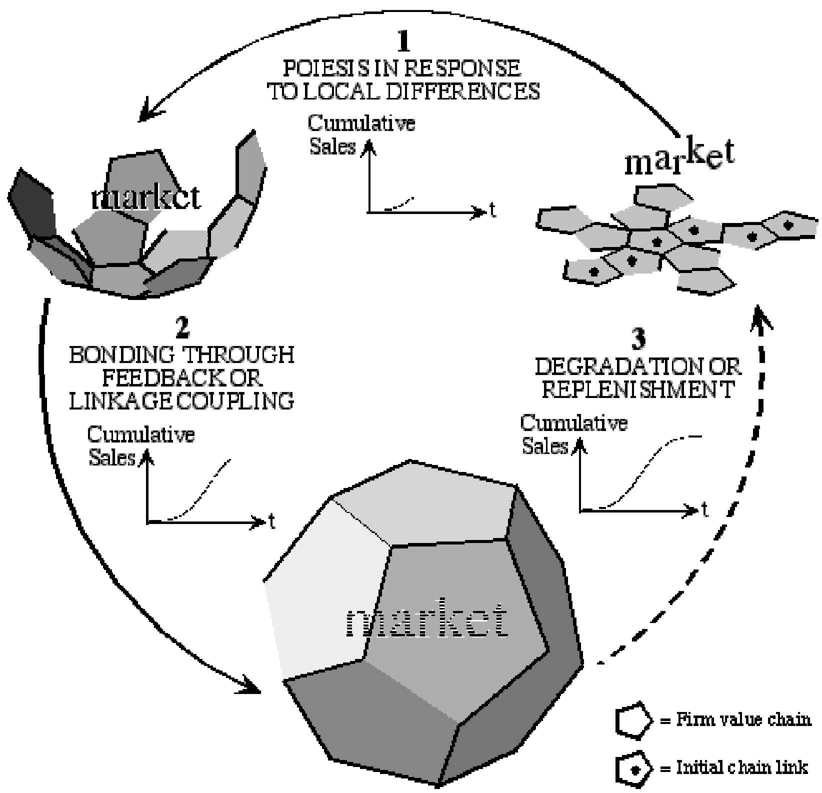
High-level learning requires multi-loop translations among language, pictures and models. The metaphorical SOS applications, which link business to science (Fig. 1) and nature (Fig. 2), do cover the translations in and between language and pictures on top of Fig. 5. Undoubtedly, these capture the imagination of business managers and scholars. Benefiting from SOS, however, requires preserving their rigor with simulation modelingthe same tool used for the advancement of SOS science itself (Holland 1997; Kauffman 1995; Turner 1997).

Explicit mathematical or simulation models are selective representations of managers' daily contact with the business reality. The relevance of modeling for learning to today's business manager, scholar and student has much to do with our struggle of defining, refining and reperceiving our daily contact with reality (Georgantzas & Acar 1995). The modeling process provides a different way of seeing managerial problems, a different mindset for thinking about business situations and for learning from their experiential ramifications. The process entails using all six translation feedback loops of Fig. 5.

VEN and SME network incumbents: A simple SOS modeling example

Modeling the autopoiesis (i.e., self-production) of small and medium enterprise (SME) networks, an integral part of the new network economy (Zeleny 2000), illustrates how simulation modeling can help us see SOS principles in action. After decades of research, market-centric SMEs are still poorly understood, despite their being the driving force of economic growth from the industrial districts of Terza Italia to the entrepreneurial cluster of American Silicon Valley, Bavarian Isar Valley, Norwegian Nordvest Forum, plus a large number of SME networks in other regions, from Australia to China to Spain. Although SMEs are driving jobs, disinflation and productivity on a global scale, they are still enigmatic with respect to what lies at the core of their success; the theory behind SMEs is absent (Zeleny 1999).

Figure 6 Circular autopoiesis in market-centric value chains (adapted from Zeleny 1999).



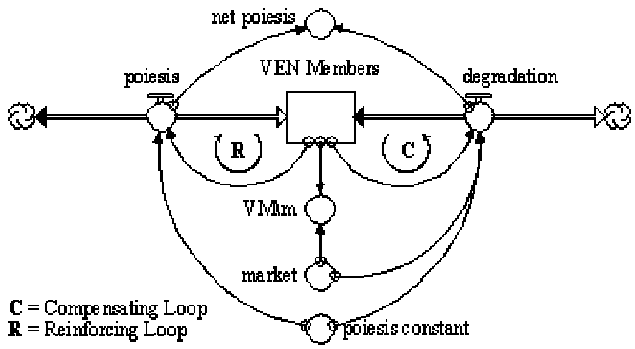
Industrial district SMEs are neither market-scattered competing clusters, nor appendices to large firms and conglomerates. On the contrary, they form their own customer- or market-centric industry value chains, enabling themselves to respond to changing markets directly, bonding with markets through customized feedback linkages (Fig. 6). SME networks and their post-modern VEN (virtual enterprise network) counterparts (Georgantzas 2000) are self-organizing systems, i.e., they meet the conditions that support self-organization in complex adaptive systems (Heylighen 1999; Zeleny 1999):

1. The circular autopoiesis of a market-centric VEN or SME network (Fig. 6) begins with poiesis (production) in response to local differences as new customers and suppliers, new technologies and goods or services enter the scene. With the market still forming (right of Fig. 6), alternative chains develop to cover needs that the initial industry value chain incumbents do not. The rules and regulations governing new entrants adhere to the requisite manifestations of the firm and industry value chain frameworks.
2. As the market grows, the network's incumbents build transforming bridges across local differences identified in the poiesis process, with the market-centric VEN or SME network components bonding through feedback or linkage coupling. The system moves toward an equilibrium state, its past behavior superseded by emergent dynamics corresponding to the network's feedback-loop linkages. Although there might still be exchange between the system and its environment, enabled by distributed control, linkages that embody its internal structure determine the network's organization and dynamics. At some point in the bonding process, equilibrium is reached when all suppliers and customers are integrated. The system then becomes organizationally closed and thermodynamically open (bottom of Fig. 6).
3. As the market declines, rules associated with degradation or replenishment come into play. During this process, incumbent firms unable to adapt go out of business, their knowledge agents absorbed into newly emerging units in new markets. As a result of degradation, new differences become significant in the system, and its self-organizing (autopoietic) process moves into the next poiesis-bonding-degradation cycle (Zeleny 1999).

With the structure and rules behind circular autopoiesis in market-centric networks understood, including birth, death, membership and acceptance, it becomes fairly simple to build a simulation model for such a SOS (Fig. 7). VEN or SME network membership, i.e., VEN Members, is a real quantity that cannot grow forever. Every system that initially grows exponentially, eventually approaches the carrying capacity of its environment, whether food supply for moose, number of people susceptible to infection, or potential market for a good or service (Sterman 2000). As an autopoietic system approaches its limits to growth, it goes through a nonlinear transition from a region where positive feedback dominates to a negative feedback dominated regime. S-shape growth often results: a smooth transition from exponential growth to equilibrium, captured by the degradation rate's logistic function (Eq. 3, Fig. 7).

Through its reinforcing (positive) feedback loop, the poiesis rate feeds the VEN Members stock (Fig. 7). Conversely, degradation depletes VEN Members via its compensating (negative) loop. Poiesis (in new entrants/month) and degradation (in incumbents/month) are generally highly variable, but keeping them independent of the VEN Members to the market carrying capacity (VM\m) ratio simplifies things. Similarly, the fixed market carrying capacity (market=50) and poiesis constant (0.8), Eq. 4 & 6 of Fig. 7, respectively, also keep the model simple. The market carrying capacity is the number of incumbent VEN Members that the market can support in a sustainable manner. Although the numerical values of these relationships would differ for different VENs or SME networks, their qualitative shape would not (Sterman 2000).

Figure 7 Structure and rules for market-centric VEN membership growth and decline. Model diagram and equations created with iThink Analyst 6 (Richmond et al. 2000).



Level Variables:
VEN Members = VEN or SME network incumbents
VEN Members_0 = 2 (1)
Rate Variables:
poiesis = poiesis constant * VEN Members (2)
degradation = (poiesis constant / market) * VEN Members^2 (3)
Auxiliary Variables/Constants:
market = 50 (market carrying capacity) (4)
net poiesis = poiesis – degradation (5)
poiesis constant = 0.8 (new entrants per unit time) (6)
VMm = VEN Members / market (7)

$t \in [0, 12]$
Computation: Runge-Kutta 4
Computation interval: dt=0.125

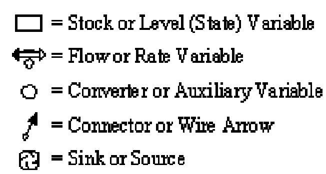
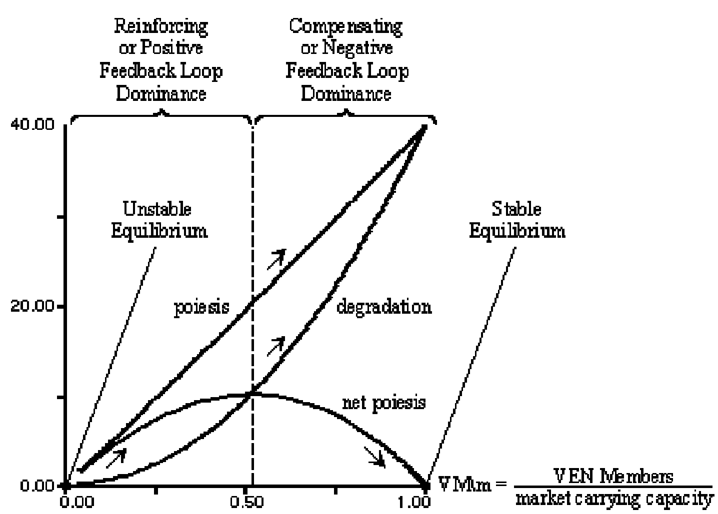


Figure 8 Phase plot for nonlinear market-centric VEN membership growth (arrows show flow direction through time). Graph created with iThink Analyst 6 (Richmond et al. 2000).

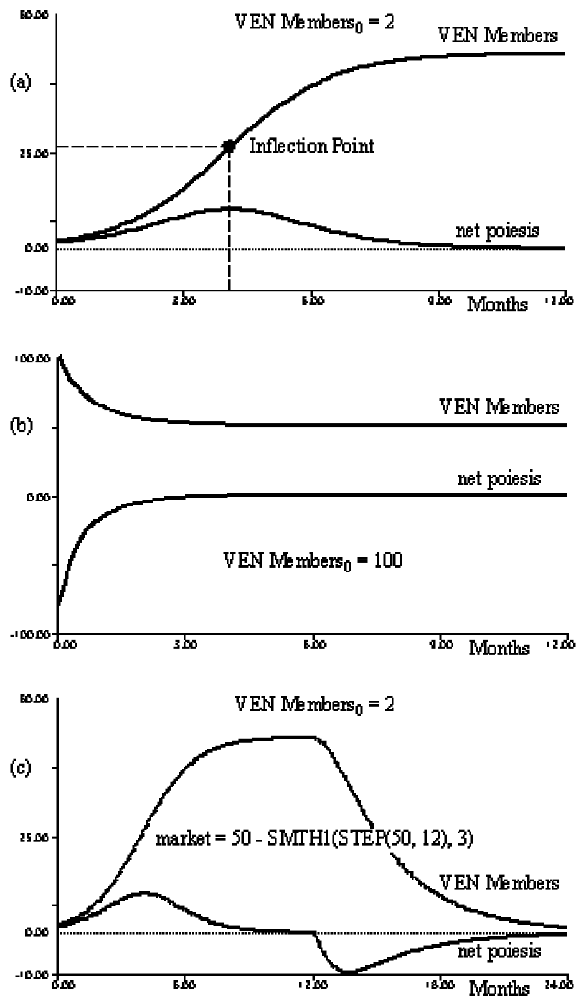


Note: Single-stock models like the one of Fig. 7 cannot oscillate to produce periodic or the nonperiodic, i.e., chaotic, dynamics Fig. 3 & 4 show.

Turning to the actual dynamics, the phase plot of Fig. 8 shows the poiesis, degradation and net poiesis curves over the VM\m ratio, with an unstable equilibrium near the VM\m=0 point. The initial VEN or SME network population is very small (Eq. 1, Fig. 7) relative to the market carrying capacity (Eq. 4, Fig. 7). Positive (reinforcing) feedback dominates the system in the region where net poiesis has a positive slope, while negative (compensating) feedback is dominant where net poiesis has a negative slope (Fig. 8). The net poiesis rate rises nearly linearly for VM<m. The behavior of the system in this region resembles pure exponential growth. As the incumbent firm population density increases, net poiesis continues to rise, but at a declining rate.

At some point, net poiesis reaches a maximum. This point comes at a lower incumbent population density than the peak in the poiesis rate because degradation is increasing at an increasing rate. The peak of the net poiesis curve on the phase plot corresponds to the inflection point in the trajectory of VEN Members in the time domain (Fig. 9a: the point at which the VEN Members stock is rising at its maximum rate).

Figure 9 Time domain for nonlinear market-centric VEN membership growth and decline. Graphs created with iThink Analyst 6 (Richmond et al. 2000).



Beyond the inflection point (Fig. 8), net poiesis, while still positive, drops, falling to zero just when the VEN or SME network incumbent population reaches the market's carrying capacity (VM=m). If the number of network incumbents exceeded their market's carrying capacity, individual firm sales and profit would become so scarce that degradation would exceed poiesis, and the number of incumbents would fall back toward the market carrying capacity. The equilibrium at VM=m or VM\m=1 is therefore stable (Fig. 8).

Figure 9 shows the behavior of the system over time for three cases:

(a) when the initial incumbent population is much smaller than the market carrying capacity,

(b) when the initial incumbent population is much larger than the market carrying capacity and

(c) when the initial incumbent population is much smaller than the market carrying capacity but, subsequently, the market declines, making the incumbent population larger than its carrying capacity.

When VM0<m, net poiesis is increasing (Fig. 9a). As long as the net poiesis slope in the phase plot is positive (Fig. 8), positive feedback dominates the system and the network's population grows exponentially. VEN Members' stock reaches maximum growth when the network's incumbents reach the inflection point on the VEN Members trajectory. At that point, the net poiesis slope is zero; the positive and negative feedback loops offset each other.

As the VEN Members stock continues to grow, the net poiesis slope in the phase plot becomes negative; negative feedback dominates the system. And the equilibrium point at VM\m=1 is stable because the net poiesis rate has a negative slope in this region (Fig. 8). A network incumbent population less than the market carrying capacity grows at a diminishing rate until it reaches the market carrying capacity (Fig. 9a).

An incumbent population, however, larger than the market carrying capacity falls until it reaches the market carrying capacity from above (Fig. 9b). Similarly, when the market declines, its incumbent firm population becomes larger than the market carrying capacity and thereby falls until it reaches the market carrying capacity from above (Fig. 9c). This is how the poiesis-bonding-degradation cycle (Fig. 6) works.

Conclusion

Distributed control among a self-organizing system's components enables globally coherent dynamics out of local component interactions. Circular or feedback-loop relationships among system components form the pathways to self-organization. The structure they create causes nonlinear SOS dynamics spontaneously. Positive feedback leads to explosive growth, which ends when all dynamics has been absorbed into an attractor, leaving the system in a stable, negative feedback state.

The new SOS science has grown out of many disparate scientific fields with many different concepts, terms and methods, applied to seemingly different types of systems. Out of all these, however, a core of fundamental ideas and principles emerges, applicable to all self-organizing systems, from simple crystals to brains to social organizations. Salient SOS characteristics intrigue business researchers and practitioners who eagerly adopt them. Consequently, SOS business applications are either metaphorical or computational.

The metaphorical SOS applications undoubtedly charm business managers and scholars, but their metaphors focus on SOS outcomes, treating self-organizing systems like black boxes. Conversely, the computational SOS applications employ the same tool used for the advancement of SOS science itself: simulation modeling. Much conducive to effective decision making through high-level learning, simulation modeling entails multi-loop translations among SOS language, pictures and models that render metaphorical black boxes transparent.

SOS metaphors are good as far as they provide a springboard for discussion about the possibilities that emerge when combining physical and social sciences. To benefit from the new

SOS science, however, business managers and researchers must preserve SOS rigor. Simulation modeling helps explain why and see exactly how SOS generate their magnificent patterns; how SOS structure causes behavior; how poiesis-bonding-degradation cycles drive the autopoietic industry value chains of VENs and SME networks. As a critical fifth scientific tool, simulation modeling perhaps can help articulate an interdisciplinary, posthumanist SOS theory that shifts between contradictory elements in old and new sciences. Yet, that might require distributed control among management scientists and practitioners themselves...

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