NORTH-HOLLAND

# Complexity Science: Implications for Forecasting

HAROLD A. LINSTONE

The whole purpose of science is to find meaningful simplicity in the midst of disorderly complexity.
Herbert A. Simon
Models of My Life (1991)

## The Curious Behavior of Complex Systems

The most exciting development in the systems area in recent years is that of complexity science, focusing on nonlinear, dynamic, complex adaptive systems (CAS). It has clearly recognized the move beyond the constraints of traditional analysis, which, in the Introduction to this issue, we termed the technical/analytic or T perspective. The Santa Fe Institute's John Casti observes that twentieth-century science has demonstrated the limits of scientific knowledge ([1], pp. 196–198). Gödel's Incompleteness Theorem, Turing's Halting Theorem, and Heisenberg's Uncertainty Principle all underscore the fact that knowledge of the real world cannot be satisfactorily attained by means of the world of mathematics *as it exists today*. But it does not mean that the human mind and its creative capability are necessarily subject to these constraints.

Nonlinear systems may be (1) stable, that is, converging to an equilibrium; (2) oscillating stably; (3) chaotic within predictable boundaries; or (4) diverging unstably. In the chaotic state the system appears to exhibit paradoxical behavior: it is deterministic because it is fixed by equations and yet it incorporates randomness. It may be orderly and suddenly become chaotic or vice versa. The system is exceedingly sensitive to initial conditions, making the use of historical data as a basis for forecasting dubious at best [2].

Casti sees complex systems as either nonadaptive or adaptive. The former are characterized by the ability to see the whole picture, permit no rule changes, and can be described effectively by available predictive mathematical models. An example is astronomy. The latter, CAS, cannot see the whole picture, permit rule creation or change, and are adaptive. They tend to be medium-sized, that is, not describable either by few variables or by a very large number (and thus not amenable to statistical approaches). As Casti admits, there is no theory yet for such systems—"we're not even

---

A version of this article was presented at the 18th International Symposium on Forecasting in Edinburgh, Scotland, 10–13 June 1998.

HAROLD A. LINSTONE is University Professor Emeritus in the Systems Science PhD Program at Portland State University in Portland, Oregon, USA.

Address correspondence to H. A. Linstone, Systems Science PhD Program, Portland State University, P.O. Box 751, Portland, OR 97207, USA. E-mail: <hwhl@odin.cc.pdx.edu>.

Technological Forecasting and Social Change 62, 79–90 (1999)

655 Avenue of the Americas, New York, NY 10010
0040-1625/99/$–see front matter
PII S0040-1625(99)00034-7

close" ([1], p. ix). He suggests that we are at a stage reminiscent of gamblers in 1600 before Pascal and Fermat developed the theory of probability.

We have already noted the counterintuitive behavior of complex systems with regard to deterministically engendered randomness. A second source of such surprising behavior is uncomputability that results in the transcendence of rules, that is, there may be no deductive rule governing a system's activity. For example, in economics, the rule of price adjustment arising from a given set of agent preferences and endowments can be any rule desired, not necessarily a rule leading to Adam Smith's invisible-hand equilibria ([1], p. 112). The specter of uncomputability has also been raised by physicist Roger Penrose in his insistence that cognition involves activities that transcend simple rule following.

A third source is instability that results in large effects from small changes (the "butterfly" effect). A fourth is connectivity, resulting in behavior that cannot be decomposed into parts. A fifth source is emergence, resulting in self-organizing patterns.

It is evident that the challenge for the forecaster is an awesome one. Better understanding of the internal dynamics of nonlinear systems is vital for more effective forecasting and it will require unprecedented insight and ingenuity.

**The Case of Logistic Growth or S Curves**

One of the most familiar forecasting tools is the logistic or Pearl or S curve. It was adapted to technological forecasting by Fisher and Pry of General Electric in a now classic paper in 1971 [3]. Its popularity is reflected in the book *Predictions* by Modis, published in 1992 [4]. It is fascinating to note that the logistic equation describing this curve as a continuous function of time becomes, in its discrete recursive form, the foundation of chaos theory:

$$dx/dt = K\,x\,(L - x) \rightarrow x_{n+1} = K\,x_n\,(1 - x_n)$$

where $x$ is the variable of interest, $t$ is the time, $L$ is the growth limit, and $K$ is a constant. The latter equation can exhibit all the four behaviors mentioned previously, that is, stability, oscillation, chaos, and unstable divergence [2]. Plotted as a function of $K$, it becomes the bifurcation diagram which displays another characteristic of nonlinear dynamic systems, fractal self-similarity. This means that the bifurcation pattern is repeated at different levels of magnification. The S curve itself leads to a fractal pattern: the envelope of a series or cascade of S curves is itself an S curve ([5], p. 63).

If we put the *solution* of the logistic differential equation (instead of the equation itself) into discrete form, we find that chaotic behavior appears at both ends of the familiar S curve (Fig. 1) [6]. The start of the chaotic phase can be increasingly anticipated when logistic growth fades, but its precise timing remains elusive. Increasing obsolescence or inadequacy of an established pattern leads to a critical situation where a minor event can suddenly push the system into chaos. The timing of the end of the chaotic phase and emergence of a new configuration is similarly uncertain. However, as it becomes increasingly stable with growing success, predictability improves dramatically.[1]

[1] Recently it has been suggested that the shift phase from one S curve to the next can be interpreted in terms of a bifurcation pattern, i.e., a sequence of forward and reverse bifurcations representing the initial explosion of new technological concepts followed by the contraction as infeasible ones are weeded out [7].

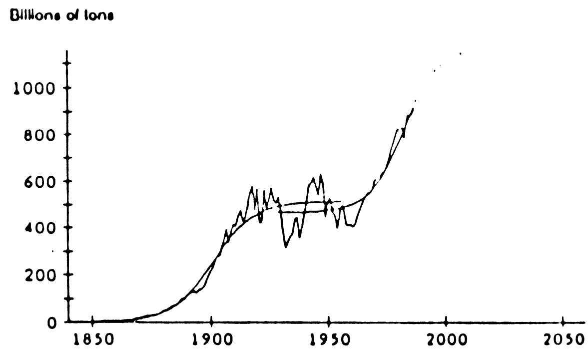


**Fig. 1. Annual U.S. production of bituminous coal (large oscillations belong to end of first curve and start of second curve). Source: [6], p. 117.**

Shermer cites the technology of the typewriter development as an example of the chaotic period preceding an S curve. Between 1714 and the 1860s at least 112 typewriters were developed, exhibiting wide diversity in design, before Stoles produced the one that led to the Remington. It would have been impossible to forecast the successful innovation and its S curve during the chaotic phase [8]. The same characteristic is observed in early bicycles and automobiles. The instances of accidental discovery are legion. For instance, the nuclear age unexpectedly produced nuclear fallout, neutron radiation, magnetic field disturbances, electromagnetic pulses creating component burn-out, and radio isotopes for medical diagnosis and treatment [9].

The existence of chaotic phases at the beginning and end of the S curve, together with the cascading series of such curves typical of technological evolution, clearly points up the constraints or "walls of unpredictability." The chaotic behavior at the start prevents us from pinpointing the take-off timing of the successful innovation. Consider the competition between Betamax and VHS formats for video cassette recorders. Initially both systems became available at the same time and sold at similar prices, leading to comparable, albeit fluctuating, market shares. This unstable situation was decided by the positive (amplifying) feedback triggered by a small gain in VHS market share, a seemingly chance event that could not have been forecast ([1], p. 88). Brian Arthur of the Santa Fe Institute recognized over a decade ago that a technologically inferior product can beat a superior one by its ability to exploit "network externalities." For example, a slight edge in marketing can lead to positive feedback: the value of the product increases as its use spreads.

Once the new technology is on its way, forecasting becomes quite feasible. Usually the S curve can be estimated well once 5–10% of the potential market has been attained. As the asymptote is approached and technological stagnation sets in, the forecaster is frustrated once more as the trigger that sets off the chaotic phase is elusive. Even so, the examination of the envelope curve, that is, the S curve at the next fractal level, gives significant insight for forecasting. It follows from this discussion that it is generally, but not always, true that short-term forecasting is more feasible than long-term forecasting. It all depends on the system phase(s) that correspond to the particular forecast time span.

## Cycles

It is evident that technological, as well as societal, advance exhibits both stable and unstable, regular and unique characteristics. One might depict a sequence of S

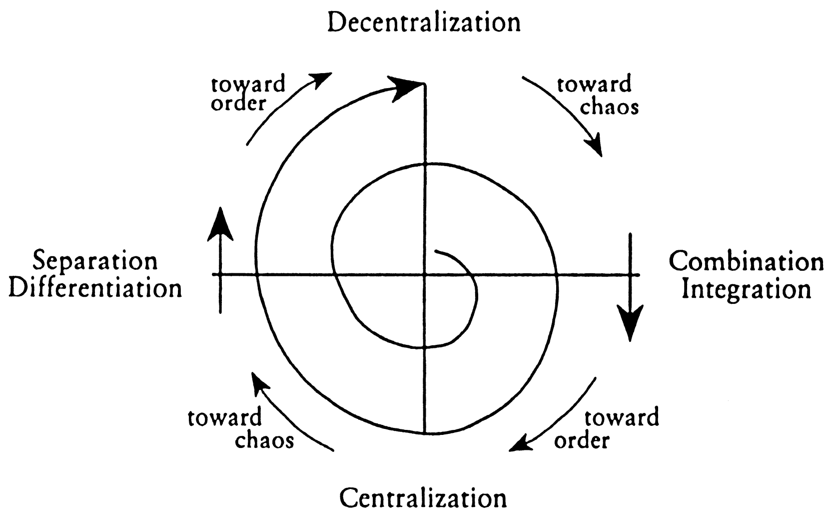


**Fig. 2. The evolution of complex systems.**

curves as a cyclic phenomenon, with stable growth followed by bounded randomness followed by stable growth, and so on. The cycles reflect significant systemic similarities, but tell us nothing about the unique factors that conjoin to trigger the phase changes. For example, an examination of the worldwide use of various forms of energy—wood, coal, oil, gas—shows that the peaks in primary reliance have shifted with a periodicity that corresponds to that of the Kondratiev long wave [10]. But looking ahead, unique and unpredictable circumstances clearly enter in attempting to forecast the role of nuclear energy in impacting this pattern. The technologies that have spearheaded the U.S. economy since 1800—railroads, steel, oil, and information technologies—similarly match that periodicity whereas the next overarching technology (biotechnology?) raises unique considerations that may galvanize the next technological era ([11], p. 151). There are some signs that suggest the long wave length may be shrinking, from 50–60 years to 30–40 years in the 21st century. The whole subject of cycles remains a highly controversial one, with orthodox T-oriented individuals, particularly economists and physicists, firmly opposed [12].

## A Case of Technological Impact: Emerging Societal Localization and Globalization

A particularly fascinating and timely issue of technology in its complex systemic setting is that of the impact of information technology on societal organization. A useful metaphor for the evolutionary growth of complex societal systems and its cyclic nature is the spiral shown in Fig. 2. There is an alternation between two stable states, centralized and decentralized or integrated and separated. A simple, hierarchical system, say, a tribe or small company, grows until it can no longer be effectively managed centrally. It then separates into smaller units with considerable local autonomy. After some time growing ineffectiveness is observed and leads to reunification. Each shift may invoke a chaotic phase. In other words, successful evolution proceeds to increasing complexity by periodic restructuring involving swings between integration and differentiation.

| | Localization | Globalization |
|---|---|---|
| Media | e-mail, desktop publishing | giant media conglomerates, CNN |
| Languages | Provençal, Catalan | global English |
| Cultures | ethnic enclaves | "McWorld" (jeans, Coca-Cola, Disney) |
| Crime | neighborhood violence | global crime syndicates |
| Conflicts | terrorism, ethnic war | nuclear war, electronic war |
| Governance | tribalism, separation (Soviet Union, Canada, Italy) | integration (European Union, NAFTA, Conference of World Regions[14]) |
| Corporations | *---coordination-intensive structures---* | |
| | internal markets<br>decentralized information services (American Airlines)<br>customization of products (clothes manufactured to order) | global alliances of enterprise units<br>global sourcing (General Motors)<br>global franchising (Hertz, Best Western) |
| | *--- the internet: consumers and e-corporations---* | |
| | individual consumer-directed rather than seller-directed purchasing on the internet | individual consumer access to worldwide market on the internet |

*---multilocal or glocal (global-local) companies---*

McDonald

local ownership
local food variations (different chicken sandwiches in UK, Germany)
regional supplies/sourcing (Poland: meat, potatoes, bread)
global management concepts
global quality standards
global sourcing (Mexico: sesame seeds)

*------------- virtual corporations -------------*

Nokia Display Products
Marketing and sales done by International Technology Associates Inc.
Customer services and tech. support done by Trillium Industries Inc.

Universities *------------- virtual universities -------------*

Monterrey Technical Institute (Mexico)
student at home location (distance-learning) — will reach 800,000 Latin Americans by 2000

**Fig. 3. Information technology and organizational change: Some examples of "glocalization."**

We find this behavior at scales ranging from business to cosmology ([11], p. 324).[2] In particular, history presents us with a cyclical pattern of this kind, from primitive clans to city-states to empires. Even American history exhibits the swing between decentralized states (18th century) and a strong national government (20th century). Today we are in the midst of another such shift: a distinct devolution of power from the federal government.

Now information technology is opening up powerful possibilities of facilitating shifts between centralization and decentralization. The convergence of telecommunications and computing technologies is at the heart of this evolving impact [13]. We see centralized organizations becoming more decentralized and vice versa. Indeed, we observe simultaneous localization and globalization as suggested in Figure 3 [11, 14].

[2] One can construct a similar spiral for chemical elements, with hydrogen at the center and the heaviest elements at the rim.

The crucial questions are: *what is the desirable balance between these two organizational states and how can information technology assist in attaining it*? In Nobel laureate Herbert Simon's words [15],

> The question is not whether to decentralize, but to what extent. . . . Once more we are trying to define a golden rule: we want to find the exact level within the organizational hierarchy—neither too high nor too low—best suited to each category of decisions.

It may well be that serious imbalance can adversely affect continued sociotechnical system evolution. For example, excessive cultural homogenization through globalization may have the same detrimental effect as a monoculture has in agriculture, exacerbating species vulnerability. Voge has used the analogy of telephone switching and finds that "switches in the ideal structure are equally distributed among all [hierarchical] levels" ([16], p. 303).

Drawing on his studies of the coevolution of biological systems and their self-organizing behavior, Kauffman has arrived at the idea that complex organizations develop best when "well-chosen" or optimally-sized local subunits, non-overlapping and semiautonomous, act in their own perceived best interest [17]. For example, a stable effective organizational size in both emerging biological and human working groups appears to be about 150.[3] Despite conflicting constraints they appear to achieve coordination and coevolve even without a central administrator ([17], p. 262). The optimal degree of decentralization or subunit size appears to be close to the transition between ordered and chaotic states, that is, "at the edge of chaos." At the same time Kauffman is acutely aware of the emergence of globalization. The real significance of these ideas for business organizations in a 21st century setting dominated by information technology is beginning to evolve. As Figure 3 shows, we are already observing coordination-intensive, global-local, and virtual structures—de facto efforts to address the crucial balance question. They portend striking new networking arrangements to assure unprecedented flexibility and dynamism.

Inevitably, they also raise new concerns. The VHS-Betamax case suggested how "network externalities" can be exploited to manipulate markets. More recently, Microsoft has recognized the power of its dominance of the personal computer (PC) operating system market (currently about 90%) in controlling the development of other technological innovations in the on-line information field. Among the possible means: bundling its Internet Explorer with Windows 95 and premature announcements of non-existent future software ("vaporware") to discourage competition. At this writing the monopoly potential is being challenged by the Antitrust Division of the U.S. Justice Department.

Another concern is the ability of the individual in the organization to coevolve with the fluid organization. The need for compatibility between individual and organization will inform the self-organizing process and affect the balance between localization and globalization in unanticipated ways. Finally, cyberspace raises the question: how will legal jurisdiction be exercised when territorial boundaries, the basis of governance, become irrelevant? For example, the rapid evolution of a global financial system without effective regulatory mechanisms in place raises the specter of financial chaos. The huge Russian money transfers and laundering operations are illustrative. The permissive Cayman Islands, population 35000, now constitute the fifth largest nation in the world in terms of booking bank loans.

---

[3] This is the group size predicted for modern man based on the relationship between group size and neocortex size for primates; Petrich cites modern examples where similar size stable social groups evolved, ranging from Microsoft to Booz, Allen & Hamilton [18].

## Modeling

Modeling constitutes a primary tool in forecasting. We recall that Forrester's system dynamics model was the basis of the well known *Limits to Growth* and the many subsequent global modeling projects undertaken in the 1970s. Complexity science underscores the weakness of these models. They can suggest basic megatrends, but, as Herbert Simon has pointed out [19]:

> The fundamental conclusion drawn from the model—that exponential growth cannot be sustained indefinitely—is entirely true, has enormous impact for public policy, and could have been inferred from textbook treatments of linear dynamic systems without any computation. . . . There may even be actual harm in carrying out such a modeling exercise. . . . It may give skeptics entirely too much ammunition for questioning even those conclusions that can be validly drawn from the model.

These models ignore the unstable, chaotic phases that accompany the catastrophes the models project and consequently their inherent unpredictability. However, more recently, the use of the computer as a laboratory tool to study complex, nonlinear dynamic systems has been opening up new paths for the forecaster. In particular, it may well become an effective methodology to deepen our understanding of systems whose elements are adaptive, such as sociotechnical systems [20].

One of the most promising approaches is the use of computer simulation to "grow" complex nonlinear dynamic systems from the bottom up [1, 21]. New worlds are created that are miniatures of the real world or true silicon worlds. The computer makes it feasible to analyze systems that consist of more than a few interacting variables but not the huge numbers that can be treated statistically (as, for example, the particles in a gas). The system elements, or agents, are intelligent and adaptive in the sense that they make decisions on the basis of simple rules, can modify the rules, or create new ones. No single agent has access to what all the other agents are doing, that is, he/she has local but not global information.

The creation of such electronic worlds can provide remarkable insights such as emergent behaviors resulting from the interaction of these agents. Microlevel interactions between individual agents and global, aggregate-level patterns and behaviors mutually reinforce each other. This bottom-up simulation approach has already been used successfully to model a variety of systems:

- Traffic in Albuquerque, New Mexico, USA, encompassing 200,000 households, 400,000 daily travelers, and 30,000 road segments—showing the appearance and disappearance of traffic jams;
- Genetic regulatory networks, involving a network of the 100,000 genes in a human body cell that switch each other on and off—exhibiting a powerful tendency to self-organization and indicating that a cell type is a stable recurrent pattern of gene expression;
- Biological systems, starting with a simple stick figure which mutates in accordance with a simple set of rules, creating a set of offspring each determined by a single mutation; the striking result is that highly complex forms evolve, including look-alikes of real primitive plants[4];
- Social systems involving primitive exchange-type economies that can test the efficient market hypothesis—with the surprising result that if the agents are at least a little bit human in their behavior, there is no reason to assume markets will perform the way economics textbooks tell us they should ([1], p. 174).

[4] Similarly, simple generative and transformational rules form the templates of all human languages.

An example of the last of these models, *Sugarscape*, should be of particular interest to forecasters. A relevant question, raised by the developers of this model, is the effect of foresight on the agents. Trading sugar and spice, they initially make their decisions based on their current holdings. If agent behavior is modified so that they can look ahead a certain number of time intervals, one finds that [21]:

> . . . clearly, some foresight is better than none in this society since the long run average foresight becomes approximately stable at a nonzero level. However, large amounts of foresight, which lead agents to take actions as if they had no accumulation . . . are less "fit" than modest amounts (p. 129).

Another potential capability is the introduction of technological innovations into *Sugarscape* as substitutes for diminishing resources and determining how they affect the economies of the traders.

Taking off from the simulation approach to biological system evolution, Kauffman raises the question whether artificial technological worlds can be created in this manner. He suspects that the variants of an innovation—many tried with one successful and the others becoming extinct—mirror biological (co)evolution ([17], Ch. 9 and 12). In other words, technological (co)evolution may be guided by the same laws as biological (co)evolution. This suggests the possibility of viewing the technological web as driving its own transformation by continual creation of new niches. Using Lisp programming language logic, "symbol string" models with simple "grammar" rules provide a means of dealing with "tools," "raw materials," and "products." The initial strings represent, say, certain renewable physical resources which produce certain goods and services. At each period thereafter, the goods and services previously invented create new opportunities to create still more goods and services and the technological frontier expands ([17], pp. 276–298). Thus one can consider, for a preset planning horizon and discount rate, the possible sequences of technological goods and services that might be created and choose the one with the highest value added. After implementation in the first year, the process is repeated each year with a "rolling horizon."

Although the grammar model is a highly simplified one, it may well provide a useful tool in studying the pattern of technological evolution and coevolution of a web of technologies. Just as in the coevolution of organisms, the processes of niche creation and combinatorial optimization seem to occur with technologies. In a similar fashion the web structure itself plays an essential role in the way the web evolves and the artifact system is transformed. Kauffman believes that this approach will show that, as the complexity of the grammar rules increases, technological diversity begets diversity and it, in turn, begets growth.

Lane [22] derives four principles from such electronic worlds:

- Chance may be decisive in the evolution of a market where two products compete (recall the VHS-Betamax case);
- Coevolution occurs in an evolutionary system, be it organism or artifact: successful strategies shift over time as relationships range from complete cooperation to complete competition; such shifts correspond to unstable periods;
- It is useful to think of organizations not merely as structures, but as processors which generate structures;
- Intelligent behaviors and decisions are not necessarily rational ones; the electronic worlds echo Simon's "bounded rationality" and underscore the relevance of multiple perspectives mentioned in the Introduction to this issue.[5]

[5] Of the three perspective types (T, O, P), only T is based on rationality, cause-and-effect, scientific logic [11, 23].

Each agent or element of the system has a unique perspective based on local information which informs his or her internal models, adaptation or creation of rules, and decisions. As Brunner has pointed out, this bottom-up approach results in an emergent aggregate behavior that makes it difficult, if not impossible, to optimize the total system. In other words, while traditional comprehensive models can make us think globally, we must act locally. This recognition constitutes a restatement of the need to augment the T perspective with other perspectives and Brunner proposes that we sweep in "ethics, law, politics, and other disciplines and professions." Corresponding to our use of O and P perspectives to augment T, he stretches the concept of "science," quoting Kaplan on the "free use of intelligence on the materials of experience" and Levi-Strauss on "the science of the concrete" [24]. Either way we must break out of the constraints of the conventional approach in dealing with complex adaptive systems.

### Perspectives on Organizations Dealing With Technological Innovation

Rycroft and Kash [25] have been inspired by complexity science to divide technological products and processes into simple and complex types. A simple one can be understood in detail by a single expert, a complex one cannot. Thus they consider four classes: simple product/simple process, simple product/complex process, complex product/simple process, and complex product/complex process.

In probing the continuing U.S. trade deficit in goods, they observe that this country does poorly in the most important category, complex product/complex process. In 1995 more than half the value of the 30 most valuable product exports globally belonged to this category. Furthermore, Japan had a $174 billion trade surplus in this category, while the U.S. had a $52 billion deficit. They find that technological complexity is growing even in products not by any standard considered high technology. For example, a traditionally simple process like seed planting has become complex, involving mechanics, electronics, optics, biotechnology, chemicals, space technology, and environmental science and technology.

We are now witnessing in innovative firms an unprecedented silent coevolution between technologies and adaptive organizational networks to produce and use them. Most importantly, creativity and innovation are imbedded in these networks. The conclusion is that technology policy must mirror this complexity and adaptability if we are to compete effectively in the global market of the 21st century. It means constant organizational learning and adjusting behavior as well as abandonment of reliance on general or universal rules of management. Cause and effect relationships are difficult to identify, and each system has unique characteristics.[6] Success in maximizing innovation with complex technologies will depend on continually adaptive private/public organizational networks.[7]

### An Agenda for the Forecaster

We are all aware that there is a difference between explanation and forecast and that both can yield useful insights for planning. Consider the following examples [27]:

Excellent forecast and excellent explanation—Newton's theory
Excellent forecast and poor explanation—quantum mechanics
Poor forecast and excellent explanation—Darwin's theory

---

[6] Thus inconsistency exists between the old industry conceptual model and the new reality.

[7] The networks blur the private/public sector organizational boundaries [26].

Rather than merely confirm the inherent limits to forecasting, complexity science should be seen as opening up new paths to reveal important insights to assist decision making. The study of the evolution of complex dynamic systems shows that the conjunction of order and chaos, stability and instability, self-organization and chance, is decisive for progress. Thus complexity science presents the technological planner and manager with challenging new tasks:

1. Try to understand and map the domains of stability, stable oscillation, chaos, and instability. What triggers the shifts from one regime to another? What can we learn from the chaotic interval? What do the "attractors" tell us? It is vital that the system state be correctly diagnosed, that is, the stability-chaos pattern be recognized. This is not always an easy task; what appears to be chaos may simply be noise.[8]
2. Recognize that random-appearing data may not be random and, conversely, a perceived pattern may actually be produced by chance [2, 29]. Thus, a local cluster of cancers may be misinterpreted as correlated with industrial pollution at specific sites.[9] Alternatively, the shift from chaotic to stable behavior suggested by the recursive data may be illusory, signifying merely a brief interlude of apparent order. Or a shift from stable to chaotic behavior is erroneously assumed to be due to disturbances external to the system. The role of randomness in innovation is vital: it creates fluctuations that act as natural seeds from which new patterns and structures grow [30].
3. Find ways to circumvent the limitations to provide improved insights. One example is the use of a metatrend such as an envelope curve to anticipate the next S curve. Another is the recognition that insights and explanations provide a means of substituting for forecast limitations. Thus the creation of high reliability organizations facilitates effective response to unpredicted crises. Examples are the Federal Emergency Management Agency, airline crisis management teams, and the U.S. Air Force Strategic Air Command airborne readiness system.
4. Recognize means to stimulate a phase change. Creativity and technological change can be triggered by creating chaos in a stagnant, stable system. Alternatively, new stable growth can be instituted by determining and supporting a promising technological approach during the chaotic phase. In other words, learn to manipulate the order/chaos phases by nudges at the right time and place [29].
5. Recognize how to delay or forestall a phase change. Inappropriate timing of the onset of chaos can be averted by cutting feedback loops in the system, and/or applying external "kicks." For example, it may be dangerous to speed up information flow when there is the potential of inducing chaos that management cannot handle [2]. On the other hand, improving feedback can enhance the agents' local information and thus the bottom-up decision making process.
6. Work with models such as *Sugarscape* to develop insight on critical questions raised by the impact of technology on society. A prime example is the question posed earlier with regard to information technology: what is the desirable balance between organizational centralization and decentralization? Models such as *Sug-*

[8] For a six-step test procedure that provides necessary conditions that must be met for chaos to exist see Cambel ([28], Chap. 11).

[9] Recall Tversky and Kahneman's Belief in the Law of Small Numbers, that is, the assumption that the pattern of a large population will be replicated in all its subsets.

*arscape* can be used to build on the work of Voge [16] and also simulate other technological changes as they affect the agents and their interactions. Insightful comparisons among emergent self-organizational patterns are then possible.

## Conclusion

Complex sociotechnical systems of concern to the forecaster inevitably involve human beings and are nonlinear, dynamic, adaptive, and emergent. It is now quite clear that such systems face inherent bounds on their mathematical describability, computability, and predictability. But it is also becoming clear that we are at the frontier of exploration in drawing on complexity science to advance our understanding of these systems in entirely new ways for the benefit of the planner and decision maker.

## References


1. Casti, J.: *Would-Be Worlds*. John Wiley & Sons, New York, NY, 1997.
2. Gordon, T. J., and Greenspan, D.: Chaos and Fractals: New Tools for Technological and Social Forecasting, *Technological Forecasting and Social Change* 34, 1–25 (1988).
3. Fisher, J. C., and Pry, R. H.: A Simple Substitution Model of Technological Change, *Technological Forecasting and Social Change* 3, 75–88 (1971).
4. Modis, T.: *Predictions*. Simon & Schuster, New York, NY, 1992.
5. Modis, T.: Fractal Aspects of Natural Growth, *Technological Forecasting and Social Change* 47, 63–74 (1994).
6. Modis, T., and Debecker, A.: Chaoslike States Can Be Expected Before and After Logistic Growth, *Technological Forecasting and Social Change* 41, 111–120 (1992).
7. Wang, C., Liu, X., and Xu, D.: Chaos Theory in Technological Forecasting, Paper presented at PICMET '99 (Portland International Conference on Management of Engineering and Technology), Portland, OR, 25–29 July 1999.
8. Shermer, M.: Exorcising Laplace's Demon: Chaos and Antichaos, History and Metahistory, *History and Theory* 34, 59–83 (1995).
9. Schelling, T. C.: Research by Accident, *Technological Forecasting and Social Change* 53, 15–20 (1996).
10. Marchetti, C.: Primary Energy Substitution Models: On the Interaction Between Energy and Society, *Technological Forecasting and Social Change* 10, 345–356 (1977).
11. Linstone, H.: *The Challenge of the 21st Century: Managing Technology and Ourselves in a Shrinking World*. State University of New York Press, Albany, NY, 1994.
12. Modis, T.: Limits to Cycles and Harmony in Revolutions, *Technological Forecasting and Social Change* 59, 33–38 (1998).
13. Gaines, B. R.: Learning Curves Underlying Convergence, *Technological Forecasting and Social Change* 57, 7–34 (1998).
14. Gardner, J. N.: Mastering Chaos at History's Frontier: The Geopolitics of Complexity, *Complexity* 3(2), 31 (1997).
15. Simon, H.: *The New Science of Management Decision*. Prentice-Hall, Englewood Cliffs, NJ, 1977, Chap. 4.
16. Voge, J.: Management of Complexity, in *The Science and Praxis of Complexity*, (Contributions to the Symposium at Montpellier, France, 9–11 May 1984). The United Nations University, Tokyo, Japan, 1985.
17. Kauffman, S.: *At Home in the Universe*. Oxford University Press, New York, NY, 1995.
18. Petrich, C. H.: Organization Science: Oxymoron or Opportunity, *Complexity* 3(4), 23–26 (1998).
19. Simon, H.: Prediction and Prescription in Systems Modeling (Presented at the IIASA Conference on Perspectives and Futures, Laxenburg, Austria, 14–15 June 1988), *Operations Research* 38, 7–14 (1990).
20. Axelrod, R.: Advancing the Art of Simulation in the Social Sciences, *Complexity* 3(2), 16–22 (1997).
21. Epstein, J. M., and Axtell, R.: *Growing Artificial Societies*. The Brookings Institution, Washington, DC, and MIT Press, Cambridge, MA, 1996.
22. Lane, D.: Models and Aphorisms, *Complexity* 1(92), 9–13 (1995).
23. Linstone, H.: *Decision Making for Technology Executives: Using Multiple Perspectives to Improve Performance*. Artech House, Inc., Norwood, MA, 1999.
24. Brunner, R. D.: Predictions and Policy Decisions, *Technological Forecasting and Social Change* 62, 73–78 (1999).
25. Rycroft, R. W., and Kash, D. E.: *The Complexity Challenge: Technological Innovation for the 21st Century*. Pinter, London, 1999.

26. Kiel, L. D.: *Managing Chaos and Complexity in Government: A New Paradigm for Managing Change, Innovation and Organizational Renewal*. Jossey-Bass, San Francisco, 1994.
27. Casti, J.: *Searching for Certainty*. William Morrow & Co., New York, NY, 1990, p. 407.
28. Cambel, A. B.: *Applied Chaos Theory: A Paradigm for Complexity*, Academic Press, San Diego, CA, 1993.
29. Gordon, T., and Greenspan, D.: The Management of Chaotic Systems, *Technological Forecasting and Social Change* 47, 49–62 (1994).
30. Resnick, M.: Unblocking the Traffic Jams in Corporate Thinking, *Complexity* 3(4), 29 (1998).

*Received 8 March 1999*