Klaus Mainzer: Complex Systems and Nonlinear Dynamics of Nature and Society

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Abstract: The theory of nonlinear complex systems has become a successful problem solving approach in the natural and social sciences. But it is necessary to distinguish the different kinds of self-organization causing the nonlinear dynamics of nature and society. In the physical sciences, self-organization means phase transitions in, near of far from thermal equilibrium. But thermodynamical self-organization is not sufficient to explain the dynamics of life and society. Genetically coded self-reproduction and the Darwinean evolution of species are examples of nonlinear dynamics in the life sciences. Learning strategies of neural networks are examples of nonlinear dynamics in brain research. Computational models are used to study the nonlinear dynamics of life and brain. Social and economic interactions are examples of nonlinear dynamics in the social and economic sciences. Computer simulation and computer experiments are essential tools to study the nonlinear dynamics of human society. Thus, computer-assisted system theory enables interdisciplinary insights in common structures of different nonlinear dynamics. Finally, system theory delivers the strategic knowledge to manage the increasing complexity in nature and society.

1. From Linear to Nonlinear Thinking in Natural and Social Sciences

What does it mean -- complexity, self-organization, and all that? These terms seem to express a certain feeling and spirit at the turn of the century. They are fashionable, but sometimes cloudy. The deeper theme, however, is *nonlinearity*. Huge areas of traditional science are based on linear thinking, often without explicitly recognizing it. For Laplace, celestial mechanics was a kind of supercomputer (*'Laplacian demon'*) to forecast and trace back each physical event of future and past with perfect precision. Nearly hundred years later, Poincare proved that all planets, stars, and celestial bodies are nonlinear in the sense that their mutual effects can lead to chaotic trajectories (*'many-bodies-problem'*). Nearly sixty years later, A. N. Kolmogorov (1954), V. I. Arnold (1963) and J. K. Moser proved their famous KAM-theorem.: Trajectories in the phase space of classical mechanics are neither completely regular nor completely irregular, but they depend sensitively on the chosen initial states ('butterfiy effect'). In the case of *deterministic chaos*, the trajectory of a system is mathematically determined, but cannot be computed in the long run because of the exponentially increasing *complexity of computation*.

2. Complex Systems and Nonlinear Dynamics of Matter

Nonlinearity is not only a necessary condition of chaos, but for the emergence of *order in complex systems*, too. In general, the complex system approach is an *interdisciplinary methodology* to explain the emergence of certain macroscopic phenomena via the cooperative ('nonlinear') interactions of microscopic elements in complex or multi-component systems. The elementary units, their position and momentum vectors, and their local interactions constitute the microscopic level of description, for instance, the interacting molecules of a liquid or gas. The global state of the complex system results from the collective configuration of the local multi-component states. At the macroscopic level, there are few collective macroscopic ('global') observable quantities like, for instance, pressure, density, temperature, entropy, pattern, form, and figure. We have to distinguish closed systems without material interchange with its environment and open systems with external interactions with its environment. If the external conditions of an open system are changed by varying certain *control parameters* (e.g., temperature, nutrition), the system may undergo a change in its macroscopic global states at some threshold value of the control parameter. Those transitions are called *phase transitions*. The suitable macrovariables characterizing this change of order are denoted as *order parameters*. Thus, the emergence or decay of order in complex systems is formally represented by the introduction or elimination of order parameters in a phase transition. Only a few of them are necessary to model the dynamics of complex systems. Thus, the use of *order parameters* at the macrostate level means an *essential reduction of modeling complexity* at the microscopic level which could not be analyzed in all details.

Phase transitions near to thermal equilibrium are called *'conservative self-organization'* creating ordered structures with low energy at low temperature. Dissipative self-organization means the phase transition of irreversible structures far from thermal equilibrium. Macroscopic patterns arise from the nonlinear interactions of microscopic elements when the energetic interaction of the dissipative ('open') system with its environment reaches some critical value. A typical example are the convection rolls (order parameter) of a fluid layer at a critical value of the control parameter (temperature). In this phase transition it cannot be forecast which of two possible rolling directions will actually be realized. This phase transition far from thermal equilibrium is modelled by a *spontaneous symmetry breaking* with two solution branches of possible directions, caused by tiny random fluctuations in the beginning of the bifurcation which is strengthened to one of the two possible rolling directions.

If the system is driven further and further away from thermal equilibrium, then we get a *complex bifurcation scheme* with many locally stable equilibria. In other cases, there are limit cycles of oscillating reactions. The phase transitions of nonlinear dissipative complex systems can be modelled by several mathematical methods. In a more qualitative way we may say that old structures become unstable, break down by changing control parameters, and new structures are achieved. In a more mathematical way the microscopic view of a complex system is described by the evolution equation of a global state vector where each component depends on space and time and where the components may mean the velocity components of fluid, its temperature field, etc. They determine *order parameters* which describe the *emerging macroscopic structures* of matter.

3. Complex Systems and Nonlinear Dynamics of Life

Obviously complex systems and phase transitions deliver a *successful formalism* to model the thermodynamic self-organization of matter (e.g. laser and solid state physics, chemistry, metereology, materials science and nanotechnology). But these methods are not reduced to special laws of physics, although its mathematical principles were discovered and at first successfully applied in physics. Thus there is *no physicalism*, but an interdisciplinary methodology to explain the increasing complexity and differentiation of forms by phase transitions. The question will be how to select, interpret, and quantify the appropriate variables of complex models in the social sciences.

Biology distinguishes the *genotype*, i.e. the microscopic DNA-code of an organism, and the *phenotype*, i.e. macroscopic features of an organisms. Biological dynamics refers to the *ontogenesis*, i.e., the growth of organisms, and the *phylogenesis*, i.e. the evolution of species. In any case we have open complex systems which can be modeled by the dynamics of (macroscopic) *order parameters* caused by nonlinear (microscopic) interactions of molecules, cells, organisms, and populations. The prebiological evolution of biomolecules is explained in several nonlinear models with autocatalytic reaction schemes. The growth of an organism is described by nonlinear equations for the aggregation of cells. Selection and mutation of Darwinian evolution can be illustrated by nonlinear models with fitness landscapes. Even the ecological systems are well-known examples of nonlinear dynamics with ecological equilibria and attractors. These studies are necessary to succeed in environmental policy.

4. Computational Systems and Nonlinear Dynamics of Brain

Life science and computer science are not only the highlights of future technologies, but they are growing together with common objects of research in *'artificial life'* and *'artificial evolution'*. Natural life on earth is organized on the molecular, cellular, organism, population-ecosystem level. Artificial life aims to find modeling tools powerful enough to capture the key concepts of living systems on these levels with increasing complexity. In the artificial life approach the distinction of genotype and phenotype is not restricted to life processes based on carbon-chain chemistry. In the theory of computability the genotype can be generalized as a set of local computational devices ('genes') which recursively generates global structures of phenotypes. *Cellular automata* are well-known computational models of self reproducing and selforganizing systems. *Genetic algorithms* are methods for moving from one population of genotypes to a new fitter population.

Today, the *artificial life* approach is not a homogeneous field of research. But it seems to provide many fruitful modeling instruments for chemical and biological research. Besides these practical applications, there is a visionary dream of AL with a hard scientific core. The factual biological evolution is only a model of a complex dynamics which is governed by highly nonlinear equations. Today, we only know some properties of these equations, and where we know them, we have no analytical tools to solve them exactly. Even numerical approximations would be restricted by their immense degree of computational complexity. Nevertheless, *computer models* may allow *computer experiments* to become familiar with possible scenarios under serveral restricted constraints. These experiences with computer experiments may be used to create particular conditions, under which new materials may construct themselves and new forms of life may organize themselves. The first steps have already been taken.

The perhaps most spectacular application of complex systems is the dynamics of the *human brain*. If the brain is regarded as a *complex system of neural cells*, then its dynamics can be modeled by the *nonlinear dynamics of neural networks*. The emergence of mental states (e.g., recognition, emotions, thoughts) is modeled by the dynamics of (macroscopic) *order parameters* of cerebral assemblies which are caused by nonlinear neurochemical interactions of neural cells in *learning strategies*. Cell assemblies with mental states are interpreted as *attractors* of phase transitions.

Obviously, the human brain is no von-Neumann-Computer with separated processor and memory. *Knowledge* is not declared by rule-based programs in processors. It is associated with complex patterns of synaptic networks produced by learning algorithms. Thus, *neuroinformatics* constructs computational neural nets simulating brain dynamics. Besides simplified homogeneous Hopfield networks with Hebbian procedures there are, for instance, Boltzmann machines with a stoachastic network architecture and backpropagation strategy. Self-organizing neural maps … la Kohonen simulate pattern recognition with Darwinian rules of learning. Nevertheless, neural nets are mainly constructed as computational models which must be simulated by conventional computers.

5. Computational Systems and Nonlinear Dynamics of Society

In *social sciences* one distinguishes strictly between biological evolution and the history of human society. The reason is that the development of nations, markets, and cultures is assumed to be guided by the intentional behaviour of humans, i.e., human decisions based on intentions, values, etc. From a microscopic view point we may, of course, observe single individuals contributing with their cultural, political, and economic activities to the collective macrostate (*'order parameter'*) of the society representing cultural, political, and economic order. But macrostates of a society are not only the sum of its parts. Their order parameters strongly influences the individuals of the society by orientating their activities, by activating or deactivating their attitudes and capabilities. This kind of feedback characterizes the *nonlinear causality* of the complex dynamics in a society. If the control parameters of the environmental conditions attain certain critical values due to internal or external interactions, the macrovariables may move into an unstable domain out of which highly divergent alternative paths are possible. Tiny unpredictable microfluctuations (e.g., actions of very few influential people, scientific discoveries, new technologies) may decide into which of the diverging paths the behavior of the society will bifurcate. But, of course, the possibility to test these models is restricted: In general, we cannot experiment with a human society. This is the point where computer science comes in: Computer simulations with changing parameters deliver useful scenarios to recognize global trends of a society under chaning conditions.

The capability to *manage the complexity of modern societies* depends decisively on an effective communication network. Like the neural nets of biological brains, this network determines the learning capability that can help mankind to manage complex knowledge. In the framework of complex systems, we have to model the dynamics of information technologies spreading in their economic and cultural environment. Thus, we speak of *informational* and *computational ecologies*. There are actually realized examples, like those used in airline reservation, bank connections, or research laboratories, which include networks containing many different kinds of computers. *Internet* and *World Wide Web* are only the first generation in the technical evolution of computational networks.

The development of our society at the turn of the century depends essentially on the *growth of science and technology*. Progress in science seems to be governed by the complex dynamics of scientific ideas and research groups which are embedded in the complex network of human civilization. Common topics of research attract the interest and capacity of researchers for greater or lesser periods of time. These *'attractors'* of research seem to dominate the activities of scientists like the attractors and vortices in fluid dynamics. When states of research become unstable, research groups may split up into subgroups following particular paths of research which may end with problem solutions or may bifurcate again, and so forth. Progress in science seems to be realized by phase transitions in a bifurcation tree with increasing complexity. Sometimes scientific problems are well-defined and lead to clear solutions of problems. But there are also "strange" and "diffuse" states like the strange attractors of chaos theory.

The increasing computational capacities of modern computers enable a new quantitative approach with *simulation experiments in social sciences*. The great advantage of dynamical models is their computer-assisted graphic illustration of several scenarios with varying parameters. These scenarios may confirm, restrict or refute the chosen model. Last but not least we need reliable support for decisions in *science policy*. Different scenarios of future developments may help us to decide where to investigate our limited resources of research budget and how to realize desirable future states of the society.

As *nonlinear systems* may be applied in different fields of research, we get general insights in the *predictable horizons* of oscillatory chemical reactions, fluctuations of species, populations, fluid turbulence, or economic processes. The emergence of sunspots, for instance, which was formerly analyzed by statistical methods of time-series is by no means a random activity. It can be modeled by a nonlinear chaotic system with several characteristic periods and a strange attractor only allowing bounded forecasts of the variations. In nonlinear models of public opinion formation, for instance, we may distinguish a predictable stable state before the public voting ('bifurcation') when none of two possible opinions are preferred, the short interval of bifurcation when tiny unpredictable fluctuations may influence abrupt changes, and the transition to a stable majority. The situation reminds us of growing air bubbles in turbulently boiling water: When a bubble has become big enough, its steady growth on its way upward is predictable. But its origin and early growth is a question of random fluctuations.

Obviously, the *complex system approach* delivers *strategic knowledge to manage nonlinear dynamics in nature and society*. It is not enough to be specialized in one field. Strategic knowledge of complexity needs insight in common and coupled processes. On the other hand, we must be aware of the specific dynamics in different fields of natur and society. Thus, according to a famous quotation of Kant, *system theory without specific knowledge of natural and social sciences is empty. But natural and social sciences without system theory is blind*.

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