

History of Complex Systems Research

2.1 Reductionist Success Stories Versus the Importance of Organization Principles

There is no doubt that the superstars of 20th century science are in atomic physics (including nuclear and particle physics) and molecular (if you wish “particle”) biology. Both disciplines were driven by searching for the constituents of the organized whole. The “take home message” of the lessons from the history of science is that methodological reductionism, the analytical decomposition of structures to parts, should be completed by searching for organizational principles, too.

2.1.1 Reductionism and Holism in Quantum Physics

Capsule history of early atomic physics

Early atomism assumed that matter is composed of indivisible and unchangeable atoms. Later it turned out that atoms were made of even smaller building blocks. First, the existence of electrons were demonstrated, and the Millikan experiment showed that its mass is very small. Since atoms have neutral charge, positive particles should also exist. When it turned out that atoms are composed of parts, models were constructed to describe the relationship among these parts. A series of atom models were created for describing the distribution of negative and positive charges. The interactions of newer and newer data led to more and more refined models. In 1904 Thomson suggested the “Plum Pudding Model”. Positively charged fluid was assumed to be the

pudding, and electrons were scattered in this fluid. Ernest Rutherford's (1871–1937) experiments led to the idea of nucleus: mass and positive charge are concentrated to very small place. Niels Bohr (1885–1962), a passionate soccer player, adopted the quantum assumptions (1900) of Max Planck (1858–1947) and Albert Einstein (1879–1955) and postulated in 1913 that electrons circulate around the nucleus without energy loss (radiation), and there are jumps from one state to another with energy changes prescribed by the Planck-Einstein formula. The quantum model of the atom takes into account the particle-wave duality of the electrons suggested by de Broglie (1892–1987). Based on this assumption the location of the electrons had a probability character. Erwin Schrödinger (1887–1961), while first tried to save the classical world view, set wave equations for the motion of electrons (1925). Instead of giving a precise, deterministic description of the motion of electrons around the nucleus, a cloud of points were derived. Max Born(1882-1970) suggested that the cloud should be interpreted as the probability of the electrons being in a certain place.

There is a direct connection between atom physics and the science of complexity, since Murray Gell-Mann has been working on both fields. Quarks (and leptons) are supposed to be the most fundamental types of particle. Quarks can not occur in isolation, they must be bound to another quark or antiquark. This phenomenon is called quark confinement. Murray Gell-Mann got the Nobel prize in 1969 for explaining the interaction of quarks by the theory called *quantum chromodynamics*. Gell-Mann's interest turned later to complex systems. He served as a founder of the Santa Fe Institute, and wrote a popular book with the title "The Quark and the Jaguar: Adventures in the Simple and the Complex" [197].

A Few Words About Quantum Mechanics

Inference phenomena measured by electron diffraction confirmed that electrons may have a wave character, so the atoms are no longer seen as *discrete* entities only, but they have also *continuous* wave nature. Quantum mechanics solved this paradox: Werner Heisenberg (1901–1976) adopted a new formalism and developed his famous uncertainty principle and quantum mechanics proved to be an extremely successful discipline.

The uncertainty principle says, that one cannot assign full precision values for certain pairs of observable variables, such as the position and momentum (i.e., mass multiplied by velocity) of a single particle at the same time even in theory, and gives a quantitative relationship for the measure of uncertainty:

$$\Delta x \Delta p \geq \frac{\hbar}{2}. \quad (2.1)$$

Here Δx and Δp are the uncertainty of the measurement of position and momentum, respectively, \hbar is the Planck constant divided by 2π .

The general implication of the relationship was that quantum mechanics is inherently indeterministic.

Broadly speaking, quantum mechanics incorporates four classes of phenomena that classical physics cannot account for: (i) the quantization (discretization) of certain physical quantities, (ii) wave-particle duality, (iii) the uncertainty principle, and (iv) quantum entanglement.

Atomism Versus Holism in Physics

The concept of wave-particle duality challenged our naive view. The naive view suggested that electrons, as other particles, are discrete, localized entities. Since things we sense directly seem to be localized and discrete, one might believe the elementary particles we do not sense directly are also localized and discrete. The *principle of local action* prescribes that if A and B are spatially distant things, then an external influence on A has no immediate effect on B.

Entanglement is one of the core concepts of current quantum physics, it challenged the universal validity of the atomism, and basically implies the separability of localized particles. In certain composite systems the state of the individual components can not be separated, so it should be considered as a holistic system.

The story goes back to the Einstein, Rosen and Podolsky (EPR) paradox, and is related to the concept of locality. EPR showed that under certain circumstances quantum mechanics violates locality. Since they did not believe that this effect, which Einstein later called “spooky action at a distance”, could really happen, they implied that quantum mechanics was incomplete.

David Bohm (1917–1994) suggested the “local hidden variable” theory. He disproved von Neumann’s analysis about the impossibility of completing quantum mechanics by introducing hidden variables. However, classical quantum physics worked well and proved to be extremely useful for calculating the behavior of the physical systems, so the whole non-locality problem was left for philosophers.

John Bell (1928–1990) following Bohm’s spirit, established an inequality, which is valid under local realism but not under quantum mechanics. Basically he suggested an experiment to decide whether or not hidden variables may exist. The intrinsic non-locality of quantum mechanics has been demonstrated

later by experiments, but there are still ongoing debates about the interpretation of these results. In any case, quantum mechanics put an end of atomism. The material world is a whole, *a whole, which is not made out of parts* [414]. To put it in another way: there are objects which are not wholly decomposed into more elementary parts.

As I learned from Péter Hráskó [242] in our first informal gathering of ELMOHA, (ELmélet-MOdel-HAgyomány in Hungarian, Theory-Model-Tradition in English): realism, locality, induction hypothesis cannot be true together. More about to laymen see Chap. 7 “How real is the real world” in John Casti’s *Paradigm Lost* [94] explains beautifully the story of the paradox of quantum reality.

Emergence and organizational principles in quantum mechanics

In some theories of particle physics, even such basic structures as mass, space, and time are viewed as emergent phenomena, arising from more fundamental concepts such as the Higgs boson or strings. In some interpretations of quantum mechanics, the perception of a deterministic reality, in which all objects have a definite position, momentum, and so forth, is actually an emergent phenomenon, with the true state of matter being described instead by a wave-function which need not have a single position or momentum.

<http://en.wikipedia.org/wiki/Emergence> (checked on 16 June 2007)

Hardcore physicists, [13, 207, 305, 120] stated that the wonderful elementary laws of physics are not sufficient to explain emerging complexity. As Anderson formulated: “the ability to reduce everything to simple fundamental laws does not imply the ability to start from those laws and reconstruct the universe”. Laughlin and Pines state that “emergent physical phenomena regulated by higher organizing principles have a property, namely their insensitivity to microscopics, that is directly relevant to the broad question of what is knowable in the deepest sense of the term”.

The debate about the indispensable role of organization principles to explain emerging complexity is not over. The reductionist method proved to be very successful. Wolfenstein feels [566] that the fundamental emerging macroscopic patterns should be understood by the fundamental physical equations.

Actually he might be right: “the solution may require a collaboration of reductionists and emergentists, if they can be persuaded to talk with one another”.

2.1.2 Reductionism and Complexity in Molecular Biology

Capsule History of Early Molecular Biology

From Mendel to the Double Helix

It is known that modern genetics started with Gregor Mendel’s (1823–1884) experiments around 1865 which led him to the discovery of heritability. The laws of heredity say that physical traits are determined by factors (what we now call genes) passed on by both parents, and that these factors are passed in a predictable pattern from one generation to the next. Mendel’s laws were re-discovered around 1900 (at the same time when Planck assumed the quantum hypothesis).

Max Delbrück (1906–1981) was a German physicist who moved to the United States in 1937, where he started to study the basic rules of inheritance in a simple organism (bacterial viruses, also called as bacteriophages, or more shortly, phages). Since there were no direct methods for studying the chemical nature of the genes, Delbrück’s speculated about the atomic structure of a gene, and explained mutation as a quantum jump, and also introduced the standard experimental techniques. The question to be answered was how heritable information is stored in cells. Proteins, composed of 20 different amino acids seemed to be much more likely candidates, than desoxyribonucleic acid (DNA), a heteropolymer built of four types of monomers. Though DNA was isolated even in the middle of nineteenth century, it was only in 1944, when Oswald Avery found that chromosomes and genes are made of DNA. Delbrück motivated one of the fathers of quantum mechanics, Schrödinger, to think on the basis of life and inheritance [460]. He assumed that the gene is like an aperiodic one-dimensional crystal. Linus Pauling (1901-1994) probably the most influential chemist of the 20th century (who applied quantum mechanical theory to explain chemical bonds) has already seen that the DNA had a helical structure. There is a (not so) controversial story that Rosalind Franklin’s (1920-1958) data obtained by X-ray crystallography (and given out without Franklin’s knowledge) played a critical role in the discovery what Watson and Crick made. As everybody knows they suggested that DNA has a double helix structure. They also adopted data which showed that among the four nucleotides there are two pairs, adenine–thymine and guanine–cytosine, which occur in equal proportions. This is called Chargaff’s rule. These data led them

to the concept of base-pairing, which was the supportive pillar of their whole argument.

Genetic Code

The problem of the genetic code was to find a relationship between DNA structure and protein structure. It turned out that tri-nucleotide units (codons) code individual amino acids. There are $4^3 = 64$ different codon combinations and it was a surprise that many codons are redundant, and an amino acid maybe coded by two or more codons. Though the genetic code shows some variations, all the genetic codes used in living creatures on the Earth show a remarkable similarity: the genetic code should have evolved in very early times.

Central Dogma, Genetic Reductionism and Their Critique

The research program of “molecular biology” suggested that the replication, transcription and translation of the genetic material should and could be explained by chemical mechanisms. Crick’s central dogma of molecular biology stated that there was a unidirectional information flow from DNA via RNA (ribonucleic acid) to proteins. First, in the process of *replication* the information in the DNA is copied. Second, during *transcription* DNA codes for the production of messenger RNA. In the third phase (*processing*) RNA migrates from the cell nucleus to the cytoplasm. Fourth, messenger RNA carries coded information via ribosomes for protein synthesis (*translation*). The schema of the central dogma is:



While the central dogma was enormously successful in discovering many detailed chemical processes of life phenomena, philosophically it suggested, as Crick himself wrote [114], that “the ultimate aim of the modern movement in biology is to explain all biology in terms of physics and chemistry”. The central dogma led to *genetic determinism*. While certain phenotypes can be mapped to a single gene, the extreme form of genetic determinism, which probably nobody believes, would state that all phenotypes are purely genetically determined. In “Not in Our Genes” [437], Richard Lewontin, a controversial combatant hero of genetics and evolutionary biology with Steve Rose and Leon Kamin attacked genetic determinism. Another hero, Richard Dawkins criticized the authors by accusing them of fighting with strawman [125]. The general validity of the central dogma was challenged and falsified by Howard Temin (1934-1994) who found that RNA can be copied to DNA by an enzyme,

called reverse transcriptase [509]. The central dogma was modified:



Temin's and (a few others') finding about reverse transcription might have more dramatic consequences if the second step, the RNA \longrightarrow protein information transfer, would be also reversible. The existence of such kind of reversibility would make the inheritance of *acquired traits* possible, i.e., the *Lamarckian* mechanism. Since the second step is not reversible, Temin's discovery did not shake molecular biology. After about an eight year fight Temin's discovery was accepted, and it contributed to the success of genetic engineering.

Genetic determinism has lost its attraction as a unique explanation for the appearance of specific phenotypic traits. After 50+ years of extensive research in molecular biology, there is a very good understanding of the intricate mechanisms that allow genes to be translated into proteins. However, this knowledge has given us very little insight about the *causal chains* that link genes to the morphological and other phenotypic traits of organisms [360]. Also, human diseases due to genetic disorders are the results of the interaction of many gene products. One generally used method to understand the performance of a complex genetic networks is the *knockout* technique. It is often applied in mice, when a single gene is deleted. Occasionally there are unexpected results: a gene that is assumed to be essential to a functions was inactivated or removed, but the knockout might have no effect, or even a surprising one. Knockout experiments implied disappointing results, partially due to pleiotropy (i.e., when a single gene influences multiple phenotypic traits), or gene redundancy (when multiple copies of the same gene can be found in the genome).

Genetic reductionism, in particular, has been abandoned as a useful explanatory scheme for understanding the phenotypic traits of complex biological systems. Genes are increasingly studied today because they are involved in the genetic program that unfolds during development and embryogenesis rather than as agents responsible for the inheritance of traits from parents to offspring.

M.H.V. Van Regenmortel:
Biological complexity emerges from the ashes
of genetic reductionism. See [532].

From Reductionism to Systems Biology

As a reaction to something that some people might have seen as the “tyranny of molecular biology”, the systems thinking has been revitalized in the last several years. Systems thinking correctly states that while reductionist research strategy was very successful, it underestimates the complexity of life. It is clear, that decomposing, dissecting and analyzing constituents of a complex system is indispensable and extremely important. Molecular biology achieved a lot to uncover the structures of many chemical molecules and chemical reactions among the molecules behind life processes. The typical molecular biologist’s approach suggests that there is an “upward causation” from molecular states to behavior. The complex systems perspective does not deny the fundamental results of molecular biology, but emphasizes other principles of biological organization. Several of these principles will now be discussed briefly.

Downward Causation and Network Causality

“Downward causation” is a notion which suggests that higher level systems influence lower level configurations. Classical molecular biology deals exclusively with upward mechanisms of causation (from simple events to more complicated ones) and neglects completely the explanatory role of downward causation. Since we know that both molecules and genes form complicated networks or feedback loops, it is difficult to defend the concept that there is nothing else in science than a linear chain of elementary steps leading from cause to effects [533]. The methodologically successful reductionism is never complete, as Popper suggested: there is always some “residue” to be explained.

The concept of downward causation was offered as a philosophical perspective to the brain-mind problem. Specifically, Roger Sperry (1913–1994) suggested that mental agents can influence the neural functioning [476, 477]. Sperry was criticized by stating that the postulate that physiological mechanisms of the brain are directly influenced by conscious processes is unclear [142]. Alternatively, it was suggested by the Hungarian neuroscientist John Szentágothai (1912–1994), that the nervous system can be considered as being open to various kinds of information, and that there would be no valid scientific reason to deny the existence of downward causation, or more precisely, a two-way causal relationship between brain and mind [499].

Robustness

Biological systems show remarkable robustness, i.e., they maintain functional performance and phenotypic stability both for external perturbation and internal fluctuations [486]. Robustness in biological systems at the cellular level

is related to the celebrated concept of “homeostasis”¹, what a biological system should show in order to survive. The interplay between negative and positive feedback is the mechanism of maintaining homeostatic robustness.

“There is no new thing under the sun”. The old – and many times well-operating – concept of homeostasis [91] suggests that a certain state of the internal medium [56] is totally maintained. The notion of homeokinesis [249, 575] was suggested to serve better than homeostasis as it captured the **dynamics** of control mechanisms for the self-maintenance of organisms. As a compromise between homeostasis and chaos, Tsuda et al. (1991) [525] assumed that biological organisms keep a “homeochaotic” state to adapt dynamically to a variable non-stationary environment. Homeochaos may play a role in evolutionary processes: it was identified as the mechanism of the evolution of symbiosis ([250]); the strong instability in low-dimensional chaos is smoothed out, and dynamic stability is sustained in high-dimensional chaos.

David Krakauer from the Santa Fe Institute, and his close colleagues have investigated the tradeoff between robustness and evolvability (see e.g., [298]) in a series of papers. Robustness is certainly a more vague concept than the mathematically precisely defined notions of stability (stability of states, orbits etc). Krakauer [297] gave a classification of different mechanisms for preserving function. One of them is modularity.

Modularity

Cells as *structural units* form functionally separable *modules* [232]. Modules have strong internal connections, and looser external connections to their environment. Cellular function should emerge from the molecular interactions taking place in cells. These functions cannot be predicted by studying the isolated components alone.²

Biochemical modules are composed of many types of molecules, such as DNA, RNA, proteins, small molecules etc. Are modules real functional elements? They probably are. One way of verifying the existence of functional modules in vivo is to reconstitute the structure/function in vitro. Certain modules, such as the ones responsible for DNA replication, protein synthesis and

¹ Pubmed search showed 155498 results on 10 April 2006, 158002 on 10 June 2006; and 172623 on 16 June 2007.

² I have heard the old biochemist joke first in a lecture by the then leading Hungarian biochemist, F. Bruno Straub. “Let’s imagine you have a simple radio set, you disassemble it, you put in a mortar and pulverize it, than you take to chromatography to see what components you find and even you may guess how much of them, and then now, you are supposed to find out how a radio in fact works.”(thanks to Jóska Lázár).

glycolysis were successfully reconstituted. There are modules for which the reconstruction from purified components is difficult, for these one possible strategy is to transplant the module into a different type of cell. The fundamental module, which makes a cell excitable, i.e., ion channels and pumps necessary to action potential generation, have been transplanted into non-excitabile cells, and made the cell excitable. So, this technique opens the possibility toward synthetic biology. A third way is reconstitution *in silico*. A celebrated example of this theoretical reconstruction is the mechanism of the signal (i.e., action potential) generation and propagation in nerve cells. Hodgkin and Huxley in 1952 assumed that some phenomenological relationship for the voltage-dependent conductance of the K^+ and Na^+ ions and described the dynamics by semi-empirical equations. That time there was no information about the structure and dynamics of ion channels which mediate the ion transport through the cell membrane. Still, a phenomenological module was sufficient to predict the signal generation.

Cellular modules are certainly not rigid, and there might be overlap between modules containing common components. A complete understanding of a module requires the synthesis of phenomenological and molecular analysis. We learned from the experience of Herbert Simon's watchmakers that modularization has an evolutionary advantage.

Modules are key intermediate structures in the organizational hierarchy of cells. It is known that some cellular components are conserved across species while others evolve rapidly. Functional modules, i.e., integrated activity of highly interacting cellular components carry out many biological functions, and they may be conserved during evolution.

It seems to be clear that in spite of the enormous success of the reductionist research strategy, biological function can very rarely be attributed to an individual molecule. Biological functions should be understood as the emergent product of interactions among different types of molecules. Also, molecular biology neglects the temporal aspects, the dynamic character of organization.

Systems biology emphasizes (i) the interactions among cell constituents and (ii) the dynamic character of these interactions. Systems biology emerged in the last several years and, partially unwittingly, returned to its predecessors, systems theory and cybernetics. The history of these early disciplines will briefly be reviewed soon, while for systems biology see Sect. 4.3.

Table 2.1. Here is a somewhat arbitrary list of disciplines and their pioneers, who contributed very much what we call now complex systems research. Game theory will be discussed in Sects. 5.5 and 9.2.2.

Discipline	Pioneers
Systems Theory	von Bertalanffy
Cybernetics	McCulloch, Wiener
Game Theory	von Neumann
Theory of Dissipative Structures	Prigogine
Synergetics	Haken
Catastrophe Theory	Thom

2.2 Ancestors of present day complex system research

2.2.1 Systems Theory

Systems theory was proposed by Ludwig von Bertalanffy (1901–1972), a biologist who worked on the basic principles of life and searched universal laws of organization.

Basic Concepts of the Systems Approach

1. The System. A system is a whole that functions by virtue of the interaction of its parts. A system is defined by its elements and the relationship among these elements.
2. Analytic and Synthetic Methods. Systems approach integrates the analytic and synthetic methods by taking into account the interaction of the system with its environment.
3. Closed versus Open Systems.
 - a) Closed systems do not interact with other systems.
 - b) Open systems interact with other systems outside of themselves.

“Living forms are not in being, they are happening, they are the expression of a perpetual stream of matter and energy which passes through the organism and at the same time constitutes it.”

Bertalanffy’s conceptual model of the living organism as an open system has had revolutionary implications for behavioral and social sciences.

Systems theory is interested in *similarities* and *isomorphism*, not in the differences of various systems. The basic assumption is that physical, chemical, biological and psychological systems are governed by the same fundamental principles. The theory partially grew up from Bertalanffy’s own studies on biological growth. According to his law of growth the temporal change of the body mass of an animal can be described by the equation:

$$L(t) = L_{\max} - (L_{\max} - L(0)) \exp(-kt), \quad (2.2)$$

where $L(t)$ is the actual mass, $L(0)$ is the initial mass, and L_{\max} is an upper limit to the growth.

Exponential growth can be detected, as he mentioned, in single bacterial cells, in populations of bacteria of animals or humans, and in the progress of scientific research measured by the number of publications, etc.

I think, the most important element in von Bertalanffy’s concept is that he emphasized the necessity of **organization principles** to understand the behavior of living organisms and social groups.

Bertalanffy worked first on theoretical biology in Vienna. While he opposed the logical positivism of the Viennese Circle, he attended their meetings. After his immigration to North America in 1950, he co-founded the Society for General Systems Research (SGSR) in 1956 among others with Kenneth Boulding.³ and Anatol Rapoport.⁴

³ Kenneth Boulding (1910–1993) suggested that economics should be investigated within the framework of general systems, and in evolutionary context.

⁴ Anatol Rapoport applied mathematical models for biological and social phenomena. He worked also in game theory, and won two competitions by his Tit-for-Tat strategy (cooperate first, then respond with the opponent’s previous answer.) See later in Sect. 9.2.2.

Bertalanffy's General System Theory:

(1) There is a general tendency towards integration in the various sciences, both natural and social.

(2) Such integration seems to be centered in a general theory of systems.

(3) Such theory may be an important means of aiming at exact theory in the nonphysical fields of science.

(4) Developing unifying principles running 'vertically' through the universe of the individual sciences, this theory brings us nearer to the goal of the unity of science.

(5) This can lead to a much-needed integration in scientific education."

2.2.2 Cybernetics

Warren McCulloch: The Real Pioneer of Interdisciplinarity

Warren McCulloch (1898–1969) was one of the Founding Fathers of the movement and scientific discipline of cybernetics, who had a particular personality, a very original individual, a polymath. He learned philosophy, became an MD, and got education in mathematical physics and physiological psychology, as well. McCulloch was an experimentalist, a theoretician, a premodern scientist, a philosopher, and maybe a magician. The interest that shaped his work and life was a question, as the title of one of his papers reflects: "What is the number that a man may know it and a man that he may know a number?" [340].

Between 1941 and 1952 (i.e., in the initial period and during the golden age of cybernetics) he was at the Neuropsychiatric Institute of the Univer-

sity of Illinois in Chicago. Then he moved to the Department of Electrical Engineering at MIT, to work on brain circuits. The abbreviation EE of the department, however, had a different meaning to him. McCulloch founded a new field of study based on this intersection of the physical and the philosophical. This field of study he called “experimental epistemology”, the study of knowledge through neurophysiology. The goal was to explain how a neural network produces ideas. (See Fig. 2.1.)

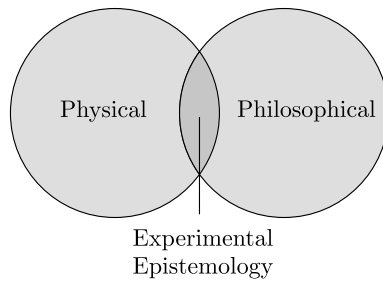


Fig. 2.1. McCulloch’s view.

His entire scientific activity was a big experiment to give a logic-based physiological theory of knowledge. Assuming that (1) the brain performs logical thinking (2) which is described by logic, the implication is that the operation of the brain could and should be described by logic.⁵

Style

The editors of the scientific journals of our age would have strong difficulties and most likely repugnance for his essayistic writings. In these articles he mixed physiology, logic, literature and psychiatry, and his personality was also involved. Demokritos, Charles Pierce, Josiah Willard Gibbs, Rudolph Magnus, Immanuel Kant, Sir Charles Sherrington, Clerk Maxwell: these names can be found on a single page of a paper on analyzing the physics and metaphysics of knowledge.

The McCulloch–Pitts (MCP) Model

In 1943 McCulloch and the prodigy Walter Pitts (1926–1969) published a paper with the title “A Logical Calculus of the Ideas Immanent in Nervous System”, which was probably the first experiment to describe the operation

⁵ McCulloch’s papers are collected with the title “Embodiments of Mind” [341].

of the brain in terms of interacting neurons [342], for historical analysis see [19, 2, 407].

The MCP model was basically established to capture the logical structure of the nervous system. Therefore cellular physiological facts known even that time were intentionally neglected.

The MCP networks are composed by multi-input ($x_i, i = 1, \dots, n$) single output (y) threshold elements. The state of one element (neuron) of a network is determined by the following rule: $y = 1$, if the weighted sum of the inputs is larger than a threshold, and $y = 0$, in any other case:

$$y = \begin{cases} 1, & \text{if } \sum_i w_i x_i > \Theta \\ 0, & \text{otherwise.} \end{cases} \quad (2.3)$$

Such a rule describes the operation of all neurons of the network. The state of the network is characterized at a fixed time point by a series of zeros and ones, i.e., by a binary vector, where the dimension of the vector is equal with the number of neurons of the network. The updating rule contains an arbitrary factor: during one time step either the state of *one* single neuron or of the *all* neurons can be modified. The former materialize asynchronous or serial, the latter synchronous or parallel processing.

Obviously, the model contains neurobiological simplifications. The state is binary, the time is discrete, the threshold and the wiring are fixed. Chemical and electrical interactions are neglected, glia cells are also not taken into consideration. McCulloch and Pitts showed that a large enough number of synchronously updated neurons connected by appropriate weights could perform many possible computations.

Since all Boolean functions can be calculated by loop-free (or feed-forward) neuronal networks, and all finite automata can be simulated by neuronal networks (loops are permitted, i.e., recurrent networks), von Neumann adapted the MCP model to the logical design of the computers. The problem of the brain-computer analogy/disanalogy was a central issue of early cybernetics, in a sense revived by the neurocomputing boom from the mid-eighties. More precisely, the metaphor has two sides (“computational brain” versus “neural computer”). There are several different roots of the early optimism related to the power of the brain-computer analogy. We will review two of them. First, both elementary computing units and neurons were characterized as digital input-output devices, suggesting an analogy at even the elementary hardware level. Second, the equivalence (more or less) had been demonstrated between the mathematical model of the “control box” of a computer as represented by the state-transition rules for a Turing machine, and of the nervous system as represented by the McCulloch-Pitts model. Binary vectors of “0”s and “1”s represented the state of the computer and of the brain, and their temporal

behavior was described by the updating rule of these vectors. In his posthumously published book *The Computer and the Brain*, John von Neumann [543] emphasized the particular character of “neural mathematics”: “. . . The logics and mathematics in the central nervous system, when viewed as languages, must structurally be essentially different from those languages to which our common experience refers. . .”

The MCP model (i) introduced a formalism whose refinement and generalization led to the notion of finite automata (an important concept in computability theory); (ii) is a technique that inspired the notion of logic design of computers; (iii) was used to build neural network models to connect neural structures and functions by dynamic models; (iv) offered the first modern computational theory of brain and mind.

McCulloch served as the chairman of a series of conferences (1946-1953) (sponsored by and named after the Macy Foundation), where at the beginning the mathematician Norbert Wiener (1894–1964) also played an important role. Cybernetics was very American. It was labeled (together with genetics) as bourgeois pseudoscience in the Soviet Union of Stalin. (I find remarkable the coincidence that there was only several days difference between Churchill’s Iron Curtain speech in Fulton and the first Macy conference on cybernetics (5 March, 8–9 March 1946). The last conference was held several weeks after Stalin’s death. Interestingly, but not very surprisingly, after the decline of cybernetics in the U.S it became popular in the Soviet scientific community. Maybe it is not literally true, that cybernetics became a dirty word in the US, but some people say, “well, it is nothing else but computer science”, others somehow identify it with robotics.

Wiener: “A Misunderstood Hero of the Information Age”?

The same year the MCP model was published, another supporting pillar of the emerging cybernetics appeared. The paper entitled “Behavior, Purpose and Teleology” by Arturo Rosenblueth, Norbert Wiener, and Julian Bigelow [443] gave the conceptual framework of **goal-directed** behavior both in technological and biological context. Looking back from now the paper is strange in several respects. It was published in *Philosophy of Science*, did not contain a single formula, figure or reference. In any case, the paper emphasized that purposeful behavior can exist both in engineered and biological systems **without** assuming the Aristotelean “final cause”. Purposeful behavior can be explained by present causes, but the causation acts in a circular manner.

The general principles of *feedback control* were understood by engineers, and autonomous control systems were used to replace human operators.

Rosenblueth worked with Walter Cannon (who popularized the concept of “homeostasis”), and he considered living processes as self-regulated ones. Wiener and Bigelow were involved in developing anti-aircraft guns by using negative feedback control during the second world war.

Cybernetics, as a scientific discipline has been named by Wiener, in his book “Cybernetics”, with the subtitle “Control and Communication in the Animal and the Machine” [558]. While the physiologists already knew that the involuntary (autonomous) nervous systems control Bernard’s “internal milieu”, Wiener extended the concept suggesting that the voluntary nervous system may control the environment by some feedback mechanisms. The theory of goal-oriented behavior promised a new framework to understand the behavior of animals, humans, and computers just under design and construction that time.

Conway and Siegelman in their book (“Dark Hero of the Information Age. In Search of Norbert Wiener, the Father of Cybernetics”) [110] analyzed how Wiener’s dark personal history led to a break among the founding fathers of cybernetics, followed by the dissolution of cybernetics into other disciplines.

Michael B. Marcus, a former student of Wiener put his supervisor’s whole activity in a different context [328]. Wiener was a well-accepted mathematician, who worked on functional analysis and on the stochastic processes before Kolmogorov gave its systematic formulation. Wiener studied a model of the Brownian motion, a classical model of the theory of stochastic processes, which is called now as the Wiener process. We also know the Wiener-Khinchine relationship, which helps to analyze stationary stochastic processes. It connects the temporal domain with the frequency domain, i.e., shows how to transform the autocorrelation function of a stationary time series to power spectrum by means of a Fourier transform. No doubt that Wiener was interested in philosophy, mathematics, mathematical physics, biology and literature. Marcus says: “There was nothing ‘dark’ about Norbert Wiener’s mathematics or morals”.

The Cybernetics Movement

The Macy conference series was organized to understand the feedback mechanisms in biological, technological and social systems, by the aid of concepts like circular causality and self-regulations. The conferences had interdisciplinary character, and Wiener and von Neumann in particular made claims that their theories and models would be of utility in economics and political science. It is interesting to note that no economist or political scientist attended any of the ten conferences. While cyberneticians spoke on behalf of physics, (well, a strange physics, not a physics of matter and energy, but a physics of infor-

mation, program, code, communication and control) there was no professional physicist among them. Max Delbrück (who was trained, as we already know, a hard core physicist, but was already working on applying physics to biology) was invited, since von Neumann felt that the arising molecular genetics will be interesting from mathematical point of view. Delbrück did not like the conference, and never returned. As Jean-Pierre Dupuy [137] analyzes, it is one of the most striking ironies in the history of science, that the big attempt of molecular biology to reduce biology to physics happened by using the vocabulary of the cyberneticians. “Cybernetics, it seems, has been condemned to enjoy only posthumous revenge” ([137], pp. 78).

The main topics of the conferences were [137]:

- Applicability of a Logic Machine Model to both Brain and Computer
- Analogies between Organisms and Machines
- Information Theory
- Neuroses and Pathology of Mental Life
- Human and Social Communication

No doubt that cybernetics was an intellectually appealing, ambitious discipline, partially victim of its own ambition. But many of its tenets survived under the names of other disciplines, and I think, cybernetics now strikes back.

Cybernetics: 50 Years After

0,1 Versus Symbol Manipulation

The members of the next generation following cyberneticians, mostly just their students, shifted the emphasis from the structural approach to the functional one. If you wish, they formulated the antithesis: “To put the scientific question, we may paraphrase the title of a paper by Warren McCulloch [340]. As Newell and Simon wrote [375]: What is a symbol, that intelligence may use it, and intelligence, that it may use a symbol?”

Consequently, the pioneers of the artificial intelligence (AI) research substituted McCulloch and Pitts’ binary strings of zeros and ones by more general symbols. Procedures on physical symbol systems were viewed the necessary

and sufficient means for general (i.e natural and artificial) intelligent action. While the symbolistic paradigm became predominant, the perspectives of the cyberneticians and AI researchers did not separate immediately, but the debate became very sharply related to the Perceptron battle.⁶ We shall tell more about the story in Sect. 5.6.

Second-Order cybernetics: Autonomous System, Role of Observer, Self-Referential Systems

It is easy to conceive that the movement of cybernetics was driven, at least implicitly, by the grand utopia that Metaphysics, Logic, Psychology and Technology can be synthesized into a unified framework. While the keywords of the early cybernetics (identified, say, with the first five meetings), were communication and control, the “second order cybernetics” (initiated by Heinz von Foerster and Roger Ashby), considered that the observer and the observed are the parts of the same system, and the result of the observation depends on the nature of their interaction.

Heinz von Foerster (1911–2002), born and raised in Vienna, who was the secretary of the last five Macy conferences. (He served between 1958-1975 as a director of the very influential Biological Computer Laboratory at the University of Illinois at Urbana-Champaign). he constructed and defended the concept of second-order cybernetics. As opposed to the new computer science and control engineering, which became independent fields, the second order cybernetics emphasized the concepts of autonomy, self-organization, cognition, and the role of the observer in modeling a system. Cybernetic systems, such as organisms and social systems are studied by an other cybernetic system, namely by the observer. Von Foerster was a radical *constructivist*. According to this view, knowledge about the external world is obtained by preparing models on it. The observer constructs a model of the observed system, therefore their interactions should be understood ”by cybernetics of cybernetics”, or “second-order” cybernetics. It is difficult to reconstruct the story, but it might be true that a set of cyberneticians, who felt the irreducible complexity of the system-observer interactions, abandoned to build and test formal models, and used a verbal language using metaphors. They were the subjects

⁶ The Perceptron is a mathematical construction of an adaptive neural network being able to learn and classify inputs. It was defined by Rosenblatt [442] by adding to the MCP rule a learning rule by modifying synaptic weights. Minsky and Papert proved in 1969 [353] that a single layer Perceptron cannot solve the “exclusive OR” problem. Perceptrons were assumed to be able to classify only linearly separable patterns. The implication of the critique was the serious restriction on funding neural network research. However, the critique is not valid for multilayer neural networks.

of well-founded critics for not studying specific phenomena [236]. Constructivism is an important element of new cognitive systems, as we shall discuss in Sect. 8.6.2.

Ross Ashby (1903-1972) [28, 29] (the latter has a freely downloadable electronic version) was probably first to use the term “self-organization”, and contributed very much to cybernetics and system science. One of his main conceptual achievements was to make a difference between an object, and a system defined on an object ([29], p. 39):

Object Versus System:

“At this point we must be clear about how a ‘system’ is to be defined. Our first impulse is to point at the pendulum and to say, the system is that thing there. This method, however, has a fundamental disadvantage: every material object contains no less than an infinity of variables and therefore of possible systems. The real pendulum, for instance, has not only length and position; it has also mass, temperature, electric conductivity, crystalline structure, chemical impurities, some radioactivity, velocity, reflecting power, tensile strength, a surface film of moisture, bacterial contamination, an optical absorption, elasticity, shape, specific gravity, and so on and on. Any suggestion that we should study ‘all’ the facts is unrealistic, and actually the attempt is never made. What is necessary is that we should pick out and study the facts that are relevant to some main interest that is already given. The system now means not a thing, but a list of variables.”

As Dupuy explains [137], cybernetics was built on the beliefs that

“1. Thinking is a form of computation. The computation involved is not the mental operation of a human being who manipulates symbols in applying rules, such as those of addition or multiplication; instead it is what a particular class of machines do – machines technically referred to as ‘algorithms’. By virtue of this, thinking comes within the domain of the mechanical.

2. Physical laws can explain why and how nature – in certain of its manifestations, not restricted exclusively to the human world – appears to us to contain meaning, finality, directionality, and intentionality.”

([137], pp. 3–4)

The mistakes of the cyberneticians led the next generation of thinkers to ignore their work. The development of a scientific theory of brain and mind was thus significantly delayed. The perspective of cybernetics now slowly returns. We discuss this question after learning more about the arguably more complex system, i.e., about the brain, in Sect. 8.6.1.

2.2.3 Nonlinear Science in Action: Theory of Dissipative Structures, Synergetics and Catastrophe Theory

From the late 1960s nonlinear science propagated from math to applied sciences. It culminated in the mid 1980s, when PCs appeared on the desk of each young researcher. Nonlinear differential equations, iterative maps, stochastic models, cellular automata, as models of many natural and social phenomena started to be investigated. New visualization tools, color coded representations of the properties of the equations were used, and people adored to play with it. Several schools competed with each other.

The *theory of dissipative structures* labeled with the name of Ilya Prigogine and his “Brussels school” grew out from the thermodynamic theory of open systems, and intended to describe the formation of (temporal, spatial and spatiotemporal) patterns first in physico-chemical, later, more ambitiously as well in biological and social systems. *Synergetics* was founded by Hermann Haken, in Stuttgart, Germany. The goal has been to find general principles governing self-organization of elements independently of their nature. A variety of disciplines such as physics (lasers, fluids, plasmas), meteorology, chemistry (pattern formation by chemical reactions), biology (morphogenesis, brain, evolution theory, motor coordination), computer sciences (synergetic computer), sociology (e.g., regional migration), psychology and psychiatry were approached. Haken’s synergetics grew up from his research in laser physics. Synergetics extended the concept of phase transition (which is a jump-like change in some variables) between so-called nonequilibrium structures. Somewhat earlier, in Bur sur Yvette, (a suburb of Paris) René Thom established catastrophe theory. One of his big goals was to explain the mathematical basis of morphogenesis of biological organisms. Though the schools did not often refer to each others’ works, there is a big overlap in the phenomena they studied. The transitions among different dynamical states are the common themes. While the theory of dissipative structures and of synergetics used both deterministic and stochastic models and emphasized the role of fluctuations in switching systems from one state to another, catastrophe theory was purely deterministic.⁷

⁷ A stochastic version of catastrophe theory was elaborated by Cobb [101]. Multistationarity in deterministic models might be associated (at least approximately), to the multimodality of stationary (being continued)

From Thermodynamics to the Theory of Dissipative Structures

Classical thermodynamics (better saying thermostatics)⁸ is interested in isolated systems, i.e., systems without being influenced by flow of matter and/or energy. The two basic laws of thermodynamics state that (1) energy is conserved; (2) physical and chemical processes degrade energy. Following Sadi Carnot⁹ the second law of thermodynamics was formulated by Clausius. He defined a measure of irreversibility, called entropy. The second law is formulated as

$$\frac{dS}{dt} \geq 0, \quad (2.4)$$

where S is the entropy and t is time.

As Boltzmann pointed out in a series of discussions¹⁰ the second law has probabilistic character. Boltzmann derived a relationship between entropy, i.e. a macroscopic quantity, and the micro states of matter. Entropy is the measure of different configurations of micro states materializing the same macro state. Macro states which could be related to more configurations are more probable, so they occur in a closed system with a higher probability. This relationship is given in his famous formula:

$$S = k \log W, \quad (2.5)$$

where k is the Boltzmann constant, and W is the thermodynamic probability (i.e., number of possible configurations) of a macro state. The extension of the theory for open systems required to define an internal entropy production dS_i/dt within the system, and dS_e/dt , which characterizes the entropy flux between the system and its environment. While $dS_i/dt \geq 0$ is postulated, the entropy flux across the border remains unspecified. There is no reason to exclude the possibility when it is negative and large, so

$$\frac{dS}{dt} = \frac{dS_i}{dt} + \frac{dS_e}{dt} \leq 0. \quad (2.6)$$

(continued from Page 45) distributions or probability density functions. It is generally assumed that (i) the number of equilibrium points in the deterministic model coincides with the number of extreme points of the density functions, (ii) equilibrium points can be associated with the location of maxima of the density functions; (iii) stable equilibrium points coincide with maxima, unstable equilibrium points coincided with minima of density functions. A change in the number of equilibrium points corresponds to the change of the extreme points in the density functions. See also Sect. 6.2.

⁸ Classical thermodynamics does NOT use the concept of time, it is a truly static theory. Its history characterized by Clifford Truesdell as tragicomical [520].

⁹ Many members of the Carnot family (an old Burgundy bourgeoisie family) are known from history of science and politics: <http://www.carnot.org/ENGLISH/carnot%20family.htm>.

¹⁰ About the debates with Zermelo see Sect. 3.3.3.

Disorder may be reducing in non-isolated systems. (Of course the total entropy, that of the open system and of the environment, would not decrease.) Energy flowing through the system makes it possible to produce “dissipative structures” in an open system, which is not possible in isolated systems. Temporal structures (such as multiple steady states, limit cycle oscillation in chemical systems), and spatial structures, such as spatial periodicity, waves and fronts were studied first in physical-chemical systems, and occasionally in social sciences as well. A specific model, i.e., the so-called Brusselator model of an oscillatory chemical system showing limit cycle behavior will be presented in Sect. 3.5.2. Here the internal process is described by nonlinear differential equations, but for the emergence of self-sustained oscillation continuous interaction with the environment is also needed.

Synergetics

Synergetics has been interested in the extension of the theory of phase transition of equilibrium states (such as between e.g., liquid and gas phases) for transitions among nonequilibrium stationary states. The characteristic variable of the transition is called the *order parameter* [228].

The basic principles of synergetics are easily illustrated in light of the example of Bénard convection (Fig. 2.2). In this case a liquid is heated from below. Since there is a temperature difference between the bottom and top surface, a macroscopic movement of the liquid begins in accordance with a specially ordered pattern. The molecules move in such a way that a rolling movement within the liquid becomes identifiable. Because of the increase in temperature, the liquid expands and the specific weight of the single molecules decreases, which implies an upward movement of the liquid elements. Up until a certain temperature, the upward movement can not overcome the internal friction. The liquid remains, therefore, in a macroscopic resting condition.

The Slaving Principle

Probably the most important concept of synergetics is the “slaving principle”. This principle connects the few numbers of macroscopic variables to the large number of microscopic ones, and ensures that dynamics can be described by a low-dimensional system. Of course, there is a bidirectional relationship between the macroscopic and microscopic variables.

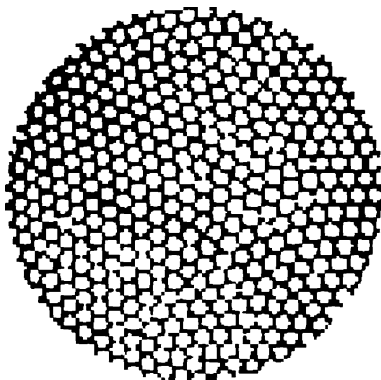
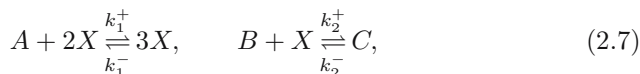


Fig. 2.2. Bénard cell: an example for a beautiful self-organized spatial patterns.

“Phase Transition” in Chemical Systems

The Schlögl model of first-order phase transition is given by the reaction



where A, B and C are external components, i.e., a component that is held at constant concentration. (This can experimentally be realized by a constant supply from a reservoir). X is the only internal component. With the notation $a \equiv (k_1^+/k_1^-)[A]$, $k \equiv (k_2^+/k_1^-)[B]$, $b \equiv (k_2^-/k_1^-)[C]$ the deterministic model is

$$-\frac{dx(t)}{dt} = x^3 - ax^2 + kx - b \equiv R(x). \quad (2.8)$$

Without the loss of generality, (2.8) could be rewritten as

$$-\frac{dx(t)}{dt} = x^3 - \lambda x - \mu, \quad (2.9)$$

since the quadratic term can always be eliminated. For the fixed points we have the equation

$$-x_{\text{eq}}^3 + \lambda x_{\text{eq}} + \mu = 0. \quad (2.10)$$

The two-dimensional parameter space can be separated into two regions by the equation defining the only triple root:

$$-4\lambda^3 + 27\mu^2 = 0 \quad (2.11)$$

An analogy with the theory of phase transitions can be seen. The phases are represented by the fixed points. The triple root may be associated with the

“critical point”. Since the constitutive equation of the van der Waals gases is also a third order polynomial, $R(x)$ can be associated with the equation

$$P = \frac{\mathbf{R}T}{V} - \frac{a_1}{V^2} + \frac{a_2}{V^3} \quad (2.12)$$

by making the following correspondences:

$$x \leftrightarrow V^{-1}, \quad k \leftrightarrow \mathbf{R}T, \quad a \leftrightarrow a_1, \quad b \leftrightarrow p,$$

where V is the volume, p is the pressure, \mathbf{R} is the Raoult constant and T is the temperature.

The curve delimiting the two “phases” (i.e., the regimes, where there are one and three solutions respectively) is shown in Fig. 2.3. Furthermore, Fig. 2.4 shows the dependence of the possible fixed points on one parameter, actually on μ , while the other parameter, λ , is fixed. The curve has a characteristic S-shape, which indicates the existence of multistationarity. More precisely, for a value μ , $\mu_1 \leq \mu \leq \mu_2$ there are three fixed points, two of them are stable, and one unstable.

It is often mentioned that there is direction-dependent phenomenon, i.e. hysteresis. This is intended to mean that the jump from the regime of the “low” fixed points to the regime of the “high” fixed points and the jump back from the “high” regime to the “low” regime does not happen at the same parameter values. The phenomenon should not be overemphasized, since the parameters

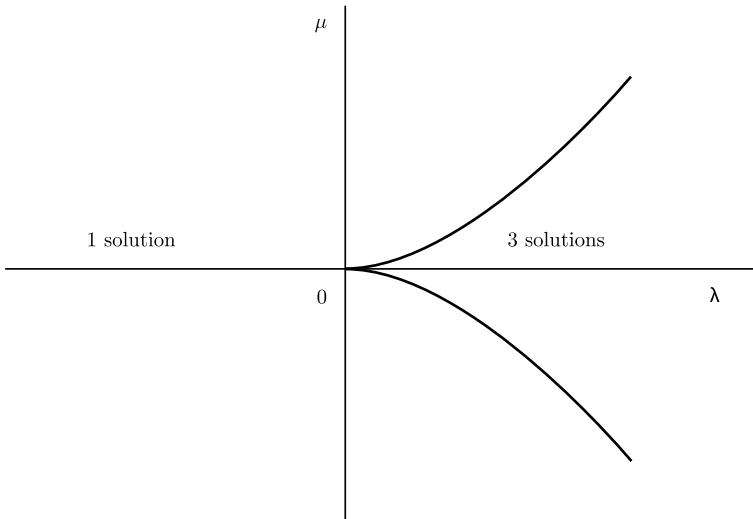


Fig. 2.3. The two-dimensional parameter space is classified into two regions (one solution and three solutions).

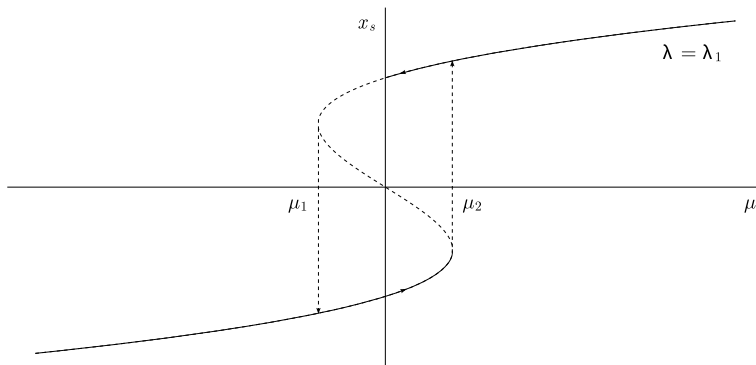


Fig. 2.4. Jumps from the regime of “low” stationary states to the regime of “high” stationary states show a hysteresis.

don’t depend on time. It is more informative to say that a bistable system can be used to classify the set (actually the interval) of the initial values. We shall go back to this question soon with catastrophe theory.

Multistable Perception

Bistability is strongly related to multistable perception of ambiguous figures. These figures have two interpretations, and the observer flip back and forth between interpretations. The Necker cube is an old example of ambiguous figures. Ambiguous patterns have common properties:

- A pattern can be perceived in two different ways.
- The time, while a perceived alternative, remains stable and is characteristic for the pattern, but may vary from person to person.
- There is no reason to assume that the two alternatives have equal strengths.
- The patterns might be subject of bias. A biased pattern may be considered as an incomplete ambiguous pattern. If the bias is stronger than a threshold, no reversion occurs.
- This threshold may be direction-dependent, and hysteresis might occur.
- Random factors determine which alternative is realized first. Priming (i.e., the showing first a strongly biased alternative) influences the result of the first perception.

- There is a transient period (1–3 min) for reaching the stationary value of the frequency of switching.
- Reversion can be influenced by conscious effort, but cannot be suppressed.

Discontinuous phase transition proved to be an appropriate model of switching between alternative percepts. Hysteresis effect (which now should be understood by looking at the figures subsequently, so real time, and history really matters - which is not (!) the case in strict bifurcation problems) can be modeled by changes in the potential landscape. [301]. Ditzinger and Haken introduced both a deterministic and a stochastic model [132, 133] for describing the oscillation in the perception of ambiguous patterns. The basic model assumes that there are two prototype patterns encoded by two linearly independent vectors, where the components of a vector encode the different features of a pattern. The state of the system is characterized by the perception amplitudes d_1 and d_2 , and the dynamics of pattern recognition for the case the two unbiased patterns are given as

$$\dot{d}_1 = d_1(\lambda_1 - Ad_1^2 - Bd_2^2), \quad (2.13)$$

$$\dot{d}_2 = d_2(\lambda_2 - Bd_1^2 - Ad_2^2), \quad (2.14)$$

where λ_1 and λ_2 are the “attention parameters”. If the attention parameters are time-independent, the recall process (governed by an appropriate potential function) leads to some fixed point attractor. However, we can assume time-dependent attention parameters with the dynamics:

$$\dot{\lambda}_1 = a - b\lambda_1 - cd_1^2, \quad (2.15)$$

$$\dot{\lambda}_2 = a - b\lambda_2 - cd_2^2. \quad (2.16)$$

Then *linear stability analysis* shows that in a certain region of the parameters there are periodic solutions, so oscillation of the perception occur. The model was extended for showing how oscillation of perception happens in the presence of a bias. Change in the bias implies different potential functions (see Fig. 2.5), which determine the recognition dynamics.

Catastrophe Theory

Catastrophe theory (CT) was fashionable in the 1970s and 1980s. It belongs to dynamical systems theory, originated from the qualitative theory of differential equations, and it is not related to apocalyptic events. The French mathematician René Thom classified the sudden jumps (called “catastrophes”) in

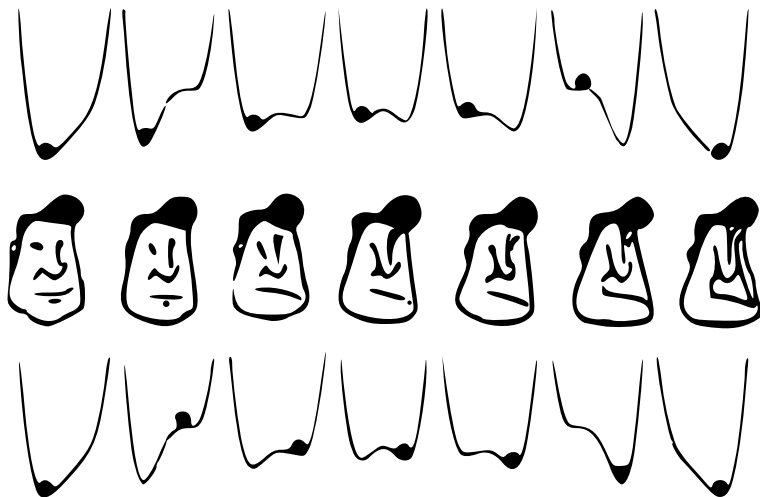


Fig. 2.5. Hysteresis effect modeled in the potential landscape. Based on Kruse et al. [301] and Ditzinger and Haken [132].

the state of certain systems due to changes in the circumstances (parameters). Actually when the number of variables is not larger than three, and the number of control parameters are smaller than or equal to five, then with one more restriction, i.e., when the dynamics is governed by a potential gradient,

$$\dot{x}(t, p) = f(x(t, p), p) = -\frac{\partial V(x(t, p), p)}{\partial p}, \quad x(0) = x_0, \quad (2.17)$$

there were only seven families of functions

$$p \mapsto \text{stationary solution}$$

(x and p denote the state vector and the parameter vector, respectively). The negative sign in the equation reflects the physical convention: a particle is assumed to move downhill in a potential well. The seven types of catastrophes were given strange names (fold, cusp, swallowtail, butterfly, hyperbolic umbilic, elliptic umbilic and parabolic umbilic). Catastrophe landscapes demonstrate that gradual and sudden changes in behavior occur in the same system under different circumstances (i.e., changes in p).

There were two types of applications of CT. First, there were low-dimensional equations, belonging to a class of gradient systems. The cubic Schlögl equation is a simple example for cusp catastrophe. Defining the potential function as

$$V = (x^4)/4 - \lambda/2x^2 - \mu x \quad (2.18)$$

and substituting to (2.17) leads to (2.9).

Second, experimental data (or more often hypothetical data) were interpreted by CT. Applied catastrophe theory's way of thinking is well represented by the next example to model oil price.

A Catastrophe Theory-Based Oil Price Model

An example on how hypothetical data was interpreted by catastrophe theory is illustrated on the example of oil-price modeling [569]. The tacit assumption is that oil prices have either low or high values, there are two separated regimes. Occasionally small changes in the circumstances imply jumps from one regime to the other. Two control parameters were defined, and the general cusp catastrophe with two control parameters were visualized in Fig. 2.6. Then there is a story which tells us the possible scenarios of the jumps. (See the caption of the figure.) The whole modeling procedure is intuitive rather than technical.

Catastrophe Theory: Was the Baby Thrown out with the Bath Water?

Catastrophe theory became the victim of its large success and maybe of the ambition of its pioneers (in addition to Thom, Christopher Zeeman, a British mathematician popularized both the theory and applications [580]). Zahler and Susmann [577] sharply criticized catastrophe theory, and most of its applications. They claimed that such kinds of modeling efforts should be restricted to science and engineering, and has almost nothing to do with biology and social sciences. While catastrophe theory disappeared from the field of applications, the celebrated mathematician Vladimir Arnold contributed to the deepening mathematical foundations of the theory [24]. The emotional attitude behind the heated debate was certainly related to the methodological discrepancies between natural and social science. However, the attack was somewhat misdirected. First, Thom and Zeeman trained and worked as mathematicians. Second, while it was true that some applications were over-dimensionalized or not justified, the attack weakened the general position of those who tried to use mathematical models in social sciences.

The Triumphant Nonlinear Dynamics: Books for Teaching

With the all the successes and misinterpretations, nonlinear dynamics, a special branch of mathematics became an extensively used framework to understand, predict and control phenomena from condensed matter physics to

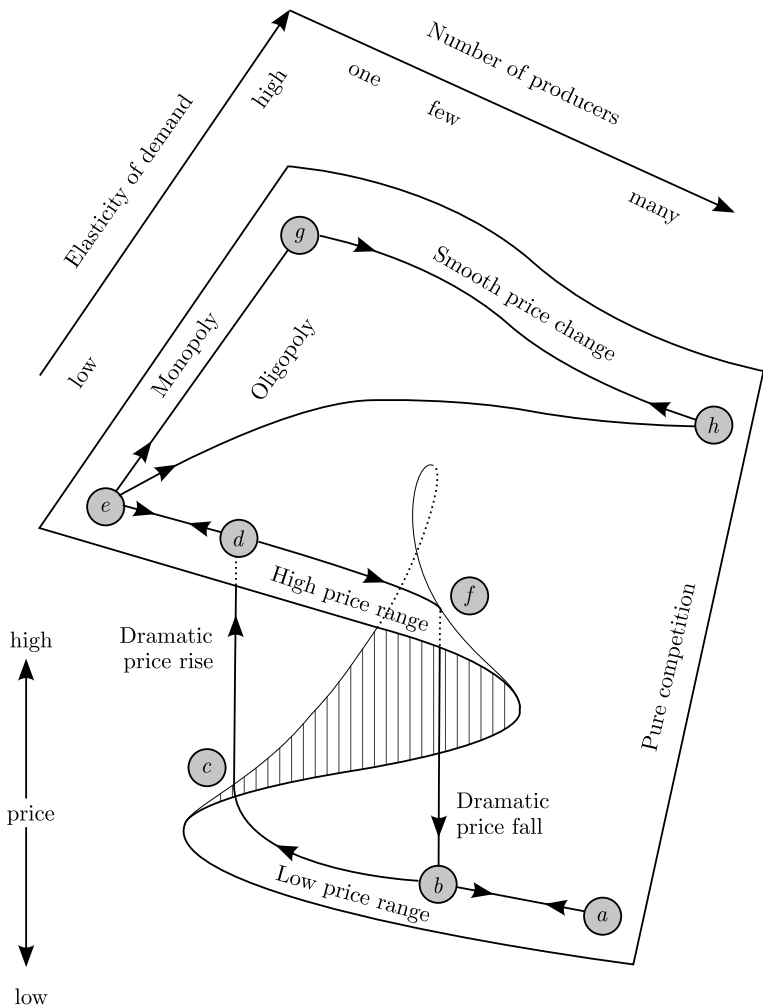


Fig. 2.6. The latitude and longitude in this case represent the elasticity of demand and level of competition in the crude oil market. The height of the landscape represents the price of oil. The model illustrates situations involving monopoly, oligopoly, and pure competition. The folded nature of the landscape surface suggests the existence of conditions supporting high and low price ranges. Paths such as $(a \rightarrow b \rightarrow c \rightarrow d \rightarrow e)$ on the landscape surface illustrate how decreasing competition can lead to sudden increases in price. Paths such as $(e \rightarrow d \rightarrow f \rightarrow b \rightarrow a)$ reflect sudden price declines due to increasing competition as new suppliers enter the market place. Increasing elasticity of demand can also lead to gradual changes in price (paths $e \rightarrow h$ and $e \rightarrow g$) under appropriate conditions. Adapted from www.kkrva.se/Artiklar/003/woodcock.html.

chemical reactions, from enzyme kinetics to population dynamics, from ecology to evolution, from brain dynamics via personal psychology to sociodynamics, and from economics back to astrophysics etc. There is no doubt, that the heroes of the last four decades contributed to these successes very much by affecting people with theories and providing them with a forum on conferences, in book series etc. One of the best textbooks was written by Strogatz [491] and it is used in many courses on nonlinear dynamics. Another excellent textbook that is also suitable for undergraduate teaching is Atlee Jackson's book [253]. Concerning the applications of nonlinear dynamics, two books published in the late eighties dominated mathematical biology, Edelstein-Keshet's and Murray's monographs [143, 368]. During the writing of this book another textbook was published by Ellner and Guckenheimer [150] and I am sure it will be popular too, since it helps to teach applied mathematics to motivated biologists.

(Non)linear models of chemical reactions (both deterministic and stochastic ones) were reviewed in our book written with János Tóth [164], while theories and experiments grown up from the observation of oscillating concentration patterns were reviewed in [152]. My experience is that Joshua Epstein's thin book [153] on transferring basic mathematical biological models (such as of population dynamics and of epidemiology) to social problems (arms race, combat, drug propagation, propagation of ideas, etc.) is first-rate. A set of papers on dynamical systems approach to social psychology was edited by [529]. The conceptual and mathematical framework of synergetics was applied to sociodynamics [552], in particular e.g., for group dynamics, opinion formation, urban evolution, etc.

The most general phenomena in nonlinear dynamical systems are the self-sustained periodic behavior. Oscillations occur in all types of systems. Clocks, pacemakers, rhythms, cycles are everywhere. But we also have to face to relentless irreversibility. The dichotomy of irreversibility and periodicity is discussed in the next chapter.