Chapter 5
Engineering

5.1 Microelectronics

5.1.1 Enzymes as "Soft-State" Nanotransistors

Molecular and cell biologists may benefit conceptually from a generalized notion of *the transistor*, an abbreviated combination of "transconductance" and "resistance," that includes *any physical device that can activate a physicochemical process when energized.* Given such a generalization, we can readily recognize two distinct classes of transistors – (1) *artificial* transistors made out of *solid-state materials* and (2) *natural* transistors, that is, enzymes, made out of *deformable* (or *soft*) *heteropolymers* of amino acids, namely, proteins and polypeptides.

Solid-state transistors conduct electricity when energized by applied voltage, while *soft-state transistors* enable or cause chemical reactions to occur when energized by substrate binding (Ji 2006e; Jencks 1975). Just as transistors are the basic building blocks of the digital computer, so enzymes are the basic building blocks of the living cell, the smallest molecular computer in Nature (Ji 1999a). This provides a theoretical framework for comparing the properties of and the physical principles underlying solid-state transistors and enzymes (see Table 5.1). A similar table was discussed in NECSI Discussion Forum (Ji 2006e).

The content of Table 5.1 is mostly self-explanatory, but the following items deserve special attention:

1. *Process*. The process enabled by a solid-state transistor when energized is the flow of electrons through it. In contrast, the process enabled by an enzyme when energized is the flow of electrons from one atomic grouping to another within a given molecule (most often a substrate) or from one molecule to another (Row 1).
2. *Size*. The linear dimension of the cell is at least 10^3 times smaller than that of the digital computer, and this is reflected in the physical dimension of enzymes relative to that of typical transistors (see Row 2).

S. Ji, *Molecular Theory of the Living Cell: Concepts, Molecular Mechanisms, and Biomedical Applications*, DOI 10.1007/978-1-4614-2152-8_5,

Table 5.1 Enzymes as self-organizing soft-state nanotransistors. Important items are highlighted

	Solid-state transistor (artificial transistor)	Soft-state transistor (natural transistor)
1. Process	Conducts electricity when energized	Catalyzes chemical reactions when energized by substrate binding
2. **Size**	*Microns (10^{-6} m)*	*Nanometers (10^{-9} m)*
3. **Mechanical property**	*Rigid (thermally immobile)*	*Deformable/soft (thermally fluctuating)*
4. Field of study	Solid-state physics	"Soft-state physics," i.e., enzymology
5. **Mechanism of energization**	*Current or voltage applied to gate*	*Substrate-binding-induced activation* of conformational substates of Frauenfelder et al. (2001)
6. Terminals	Input (source, emitter)	Reactants
	Trigger (gate, base)	Enzyme
	Output (drain, collector)	Products
7. Electron flow	10^5 electrons per switching event (mega-electron transistor)	One electron per switching event (single-electron transistor)
8. **Component connection**	*Static and artificially organized (covalent bonds, 50–100 kcal/mol)*	*Dynamic and self-organizing (Sect. 3.1) (noncovalent bonds, 1–5 kcal/mol)*
9. **Mobile objects**	*Electrons*	*Molecules*
	Holes	*Ions*
	Phonons	*Conformons (Chap. 8)*
10. Number of units in a logical gate	~20	1 ~ 50
11. Number of units in a processor	$\sim 10^{11}$	$\sim 10^9$
12. **Behavior**	*Deterministic (binary, crisp logic)*	*Nondeterministic (multivalued, fuzzy logic)*

3. *Deformability*. Traditional transistors are rigid and large enough to resist the randomizing effects of thermal motions of the structural components of a transistor. Enzymes are flexible (i.e., soft) and small enough to undergo thermal fluctuations or Brownian motions that are essential for their functions (Ji 1974a, 1991) (Row 3). This is why enzymes can be viewed as "soft-state transistors," the study of which may be referred to as "soft-state physics" (e.g., enzymology) in contrast to solid-state physics. Examples of soft-state physics include the study of protein folding, single-molecule enzymology (Xie and Lu (1999); 2001), the informatics of biopolymers, and artificial polymers with mechanically activatable chemical moieties (Lenhardt et al. 2010).
4. *Self-organizing circuits*. Solid-state transistors are fabricated by humans, while soft-state transistors have resulted from spontaneous chemical reaction-diffusion processes or *self-organizing processes* (Prigogine 1977, 1980) selected by biological evolution. The principle of self-organization is rooted in (1) the dissipation of free energy and (2) the principle of structural complementarity as exemplified by the Watson-Crick base pairing and the enzyme-substrate complex

formation and applies not only to the interactions among the components of a soft-state transistor (Row 8) but also to the interactions among a set of soft-state transistors needed to construct logical gates and processors (Rows 10 and 11). In both intra- and inter-transistor interactions, solid-state transistors utilize strong, *covalent bonds* (50 ~ 100 kcal/mol), whereas soft-state transistors depend mainly on weak, *noncovalent bonds* (1–5 kcal/mol) (Row 8).

These weak interactions, coupled with the principle of structural complementarity, appear to be necessary and sufficient for the production, operation, and destruction (after their task is completed) of self-organizing biological circuits of soft-state transistors which then can be identified with hyperstructures and SOWAWN machines (Sect. 2.4) or bio-quantum dots (see Table 4.7).

5. *Logic*. The behavior of solid-state transistors are deterministic, obeying the Aristotelian or binary logic of the excluded middle. The behavior of a soft-state transistor, however, is nondeterministic and fuzzy (Sect. 4.6) (Ji 2004a) because of its structural deformability and thermal fluctuations, giving rise to not one but a range of rate constants per enzyme distributed nonrandomly (see the histogram of waiting times in Fig. 11.24) (Lu et al. 1998) (Row 12).

5.2 Computer Science

5.2.1 The Principle of Computational Equivalence and a New Kind of Science (NKS)

This principle proposed by Dr. Stephen Wolfram in 2002 states that all rule-governed processes, whether natural or artificial, can be viewed as *computations*. According to Wolfram (2002), it is possible to model any complex structure or phenomena in nature using simple computer programs (or algorithms) based on cellular automata that can be applied n times repeatedly (or recursively), where n ranges from 10^3 to 10^6. In other words, underlying all complex phenomena (including living processes), there may exist surprisingly simple sets of rules, the repetitive application of which inevitably leads to the complex phenomena or structures found in living systems. The following set of quotations from his book, *A New Kind of Science* (Wolfram 2002), illustrate his ideas:

> Three centuries ago science was transformed by the dramatic new idea that rules based on mathematical equations could be used to describe the natural world. My purpose in this book is to initiate another such transformation, and to introduce a new kind of science that is based on the much more general types of rules that can be embodied in simple computer programs. . . . If theoretical science is to be possible at all, then at some level the systems it studies must follow definite rules. Yet in the past throughout the exact science it has usually been assumed that these rules must be ones based on traditional mathematics. But the crucial realization that led me to develop the new kind of science in this book is that there is in fact no reason to think that systems like those we see in nature should follow only such traditional mathematical rules [p. 1]. (5.1)

When mathematics was introduced into science it provided for the first time an abstract framework in which scientific conclusions could be drawn without direct reference to physical reality. Yet, despite all its development over the past few thousand years, mathematics itself has continued to concentrate only on rather specific types of abstract systems – most often ones somehow derived from arithmetic or geometry. But the new kind of science that I describe in this book introduces what are in a sense much more general abstract systems, based on rules of essentially any type whatsoever.

One might have thought that such systems would be too diverse for meaningful general statements to be made about them. But the crucial idea that has allowed me to build a unified framework for the new kind of science that I describe in this book is that just as the rules for any system can be viewed as corresponding to a program, so also its behavior can be viewed as corresponding to a computation.

Traditional intuition might suggest that to do more sophisticated computations would always require more sophisticated underlying rules. But what launched the whole computer revolution is the remarkable fact that universal systems with fixed underlying rules can be built that can in effect perform any possible computation. . ..

But on the basis of many discoveries I have been led to a still more sweeping conclusion, summarized in what I call the Principle of Computational Equivalence (PCE): that whenever one sees behavior that is not obviously simple – in essentially any system – it can be thought of as corresponding to a computation of equivalent sophistication . . . it immediately gives a fundamental explanation for why simple programs can show behavior that seems to us complex. For like other processes our own processes of perception and analysis can be thought of as computation. But though we might have imagined that such computations would always be vastly more sophisticated than those performed by simple programs, the Principle of Computational Equivalence implies that they are not. And it is this equivalence between us as observers and the systems that we observe that makes the behavior of such system seem to us complex [pp. 4–6]. (5.2)

The key unifying idea that has allowed me to formulate the Principle of Computational Equivalence is a simple but immensely powerful one: that all processes, whether they are produced by human effort or occur spontaneously in nature, can be viewed as computations. . . . it is possible to think of any process that follows definite rules as being a computation – regardless of the kinds of elements it involves. . ..

So in particular this implies that it should be possible to think of processes in nature as computations. And indeed in the end the only unfamiliar aspect of this is that the rules such processes follow are defined not by some computer program that we as humans construct but rather by the basic laws of nature.

But whatever the details of the rules involved the crucial point is that it is possible to view every process that occurs in nature or elsewhere as a computation. And it is this remarkable uniformity that makes it possible to formulate a principle as broad and powerful as the Principle of Computational Equivalence. . .. For what the principle does is to assert that when viewed in computational terms there is a fundamental equivalence between many different kinds of processes. . .. [pp. 715–716]. (5.3)

[This statement is almost identical to the idea of universal computation advocated by S. Lloyd (2006).]

The traditional mathematical approach to science has historically had its great success in physics – and by now it has become almost universally assumed that any serious physical theory must be based on mathematical equations. Yet with this approach there are still many common physical phenomena about which physics has had remarkably little to say. But with the approach of thinking in terms of simple programs that I develop in this book it finally seems possible to make some dramatic progress. And indeed in the course of the book we will see that some extremely simple programs seem able to capture the essential

> mechanisms for a great many physical phenomena that have previously seemed completely mysterious [p.8]. (5.4)

> . . . traditional mathematical models have never seemed to come even close to capturing the kind of complexity we see in biology. But the discoveries in this book show that simple programs can produce a high level of complexity. And in fact it turns out that such programs can reproduce many features of biological systems – and seem to capture some of the essential mechanisms through which genetic programs manage to generate the actual biological forms we see. [p. 9]. (5.5)

> Over and over again we will see the same kind of thing: that even though the underlying rules for a system are simple, and even though the system is started from simple initial conditions, the behavior that the system shows can nevertheless be highly complex. And I will argue that it is this basic phenomenon that is ultimately responsible for most of the complexity that we see in nature. [p. 28]. (5.6)

> . . . intuitions from traditional science and mathematics have always tended to suggest that unless one adds all sorts of complications, most systems will never be able to exhibit any very relevant behavior. But the results so far in this book have shown that such intuition is far from correct, and that in reality even systems with extremely simple rules can give rise to behaviors of great complexity. [p. 110]. (5.7)

It may be asserted here that Statements (5.6) and (5.7) apply to biology. If so, these statements would represent the most important contributions that Wolfram has made to biology. Based on his numerous computer experiments, often involving millions of iterations of a set of simple rules applied to simple initial conditions, Wolfram concluded that complex structures can arise from simple programs. For example, he was able to simulate complex structures and processes such as the shapes of shells (Fig. 5.1) and trees and turbulence, using simple rules governing the behavior of cellular automata, from which he inferred that all complex structures and phenomena in nature can originate from recursive operations of sets of simple rules. The similarity between the computer-generated shell shapes and the real ones shown in Fig. 5.1 is striking and seems to provide credibility to Wolfram's assertions, i.e., Statements (5.1)–(5.7).

Although I do agree with Wolfram that his NKS does have the ability to represent or simulate certain complex phenomena in nature that could not even be approached using traditional mathematical tools, I suggest that both the traditional mathematics and NKS may still be subject to the constraints of the *cookie-cutter paradigm* described in Sect. 2.3.9. That is, no matter which model one adopts, either traditional mathematical or NKS, models always cut out only those aspects of reality that fit the model (i.e., the cookie cutter) and leave behind "holes" and the rest of in the dough that are beyond the capability of the models employed. We may depict this idea as shown in Fig. 5.2.

5.2.2 *Complexity, Emergence, and Information*

Ricard (2006) defines a complex system as a composite system whose properties or degrees of freedom cannot be predicted from those of its components. In other

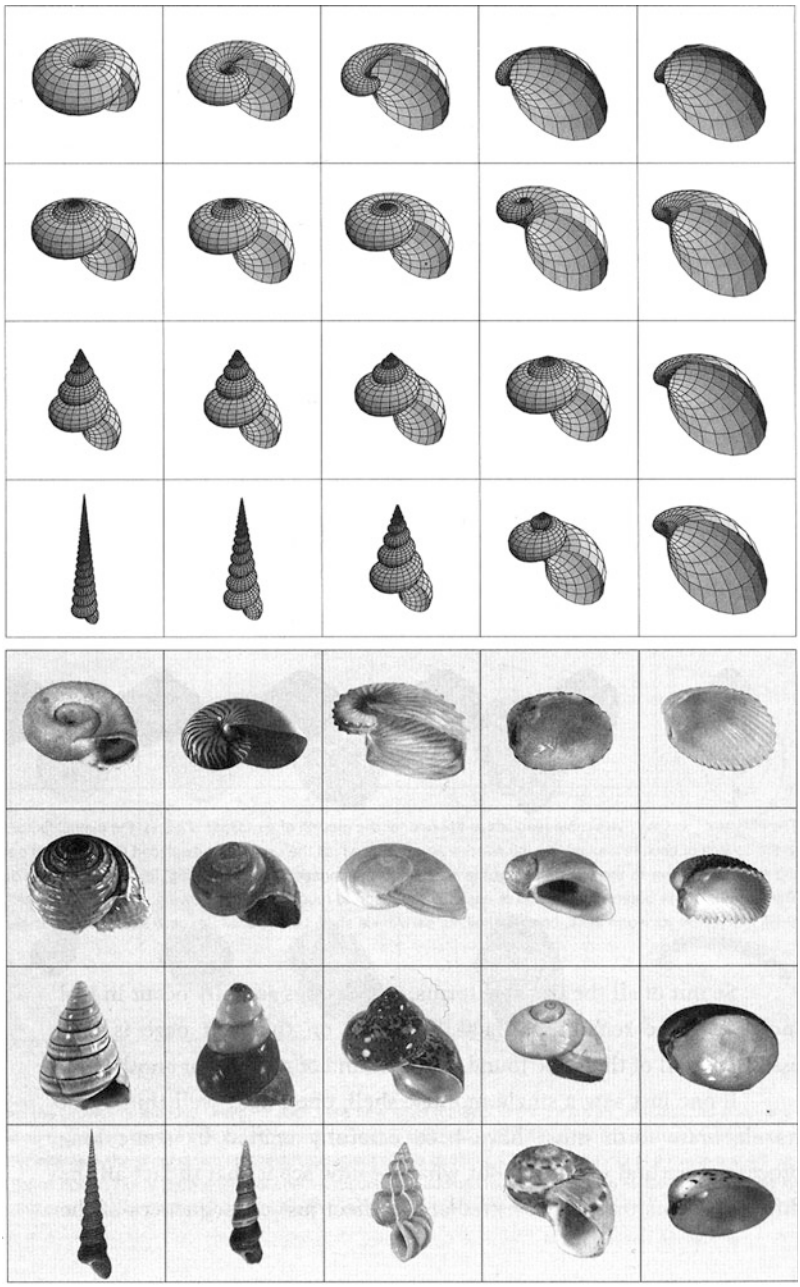

Fig. 5.1 Shell shapes generated by the simple cellular automaton models (see the *top four rows*) and found in nature (see *bottom four rows*). Two parameters are systematically changed: (**a**) the overall factor by which the size increases in the course of each revolution and (**b**) the relative amount by which the opening is displaced downward at each revolution (Reproduced from Wolfram 2002, p. 416. With permission)

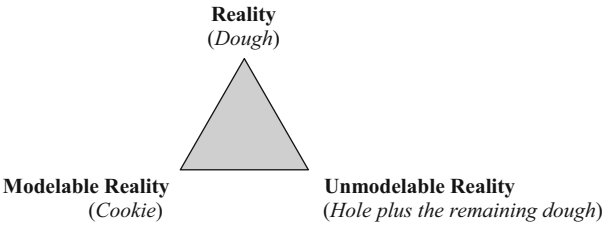

Fig. 5.2 Reality as the complementary union of the *modelable* and *unmodelable*

words, a complex system, according to Ricard, is a system that has "more potential wealth, or more degrees of freedom" than its component sub-systems or displays "properties that are emergent relative to those of the component sub-systems." He represents his idea formally as follows:

$$H(X, Y) > H(X) + H(Y) \tag{5.8}$$

where H(X,Y) is a mathematical function that describes the properties of a system XY made up of two sub-systems X and Y, and H(X) and H(Y) are the mathematical functions that describe the properties of X and Y, respectively. In short, the system XY is complex because its properties cannot be explained in terms of the sum of the properties of X and Y.

Since the concept of emergence is intrinsic to any complex system, according to Ricard, it would follow that the mechanisms of emergence would be synonymous with the mechanisms of complexification. So, Inequality 5.8 can be re-expressed using the concept of mechanisms:

$$X + Y \xrightarrow{\text{Mechanism}} XY \tag{5.9}$$

Thus, Process 5.9 can be viewed either as the mechanism of emergence or that of complexification.

One major difference between Inequality 5.8 and Process 5.9 may be that the former emphasizes the phenomenological and information-theoretic aspects, while the latter brings out the mechanisms and kinetic/dynamic aspects of the process of emergence and complexification that entails dissipation of free energy.

The terms, *complexity, emergence,* and *information*, frequently occur together in many contemporary discourses in natural, computer, and social sciences, but the relation among them appears not to have been clearly defined as yet, to the best of my knowledge. To rigorously define the relation among these terms, it may be helpful to utilize a table organized according to the triadic metaphysics of Firstness, Secondness, and Thirdness of C. S. Peirce (see Sect. 6.2) as shown in Table 5.2. The table is constructed on the basis of the assumption that *complexity* can be identified with Firstness, *emergence* with Secondness, and *information* with Thirdness.

Table 5.2 A Peircean triadic relation among complexity, emergence, and information suggested based on Peircean metaphysics. According to Peirce, all phenomena (or appearances) have three inseparably fused aspects termed Firstness (e.g., feeling, potentiality), Secondness (e.g., actuality, interactions), and Thirdness (e.g., relation, representation). The symbol "1" stands for the identity relation

	Firstness (Complexity)	Secondness (Emergence)	Thirdness (Information)
Complexity	1	Evolution	Subjective information (formal information, temperature-independent)
Emergence	Evolution	1	Objective information (physical information, temperature-dependent)
Information	Subjective information	Objective information	1

Table 5.2 is a 3 × 3 matrix which is symmetric with respect to the diagonal because the relation between any two elements of the table is commutative (e.g., the relation between complexity and information is the same as the relation between information and complexity). This leaves only three cells or relations in the interior of the table (out of the total of 3 × 3 = 9) left to be defined:

1. *Evolution* = It is the relation between *complexity* and *emergence*. Evolution refers to the *mechanism* by which certain properties of material entities are manifested both synchronically and diachronically (Sect. 4.5), which are novel relative to the properties of the interacting entities. In this view, what emerges may be thought to be not complexity but rather novelty, since complexity as the Firstness of Peirce is *intrinsic to reality itself*.
2. *Subjective information* = The information that depends on the workings of the human mind. For example, UV photons cannot carry any information to the human eye but can do so to the UV-sensing eyes of certain nonhuman brains. The historical information contained in the Bible is understood only by humans but not by nonhuman species and is furthermore temperature-independent. That is, raising the temperature of the Bible from room temperature by, say, 30°C would not change the biblical information content whereas the entropy content of the book will increase (see the "Bible test" described in Footnote c in Table 4.3).
3. *Objective information* = The information that exists independently of the human mind. Examples include the information encoded in the universal constants such as the speed of light and the electronic charge, the information encoded in the microstates of matter which is temperature-dependent to varying degrees.

One of the reasons for the difficulty in defining the three terms appearing on the margins of Table 5.2 may be traced to the fact that one of these terms, "information," occurs both on the *margins* and the *interior* of the table. What makes the situation even more difficult is the appearance of the two different kinds of information in the interior of the table – *Objective* and *Subjective* information. Thus, there are three different kinds of informations appearing in Table 5.2, reminiscent of the numerous

kinds of energies in physics – thermal, kinetic, potential, chemical, mechanical, nuclear, Gibbs free energy, and Helmholtz free energy, etc. Little confusion arises in distinguishing different kinds of energies in physics because of the availability of the principles of classical mechanics, quantum mechanics, statistical mechanics, and thermodynamics. To be able to differentiate among different kinds of information in biology, computer science, and philosophy on the one hand and between informations and energies on the other, it may be essential to utilize not only the laws and principles of physics and chemistry but also those of *semiotics*, the study of signs as developed by Peirce (1903) more than a century ago (see Sect. 6.2).

5.2.3 *Two Kinds of Complexities in Nature: Passive and Active*

We can recognize two kinds of "complexities" in nature – *active* and *passive*, in analogy to *active* and *passive* transport. For example, snowflakes (Fig. 5.3) exhibit *passive* complexity or complexification, while living cells (see the book cover) exhibit *active* complexity in addition to passive complexity. Unlike passive complexity, active complexity is exhibited by living systems utilizing free energy, and organisms with such a capability is thought to be more likely to survive *complex* environment than those with passive complexity only. According to the Law of Requisite Variety (LRV) (Sect. 5.3.2), no simple machines can perform complex tasks. Applying LRV to cells, it can be inferred that

No simple cells can survive complex environment. (5.10)

If this conjecture is true, it is not only to the advantage of cells (both as individuals and as a lineage) but also essential for their survival to complexify (i.e., increase the complexity of) their internal states.

One strategy cells appear to be using to complexify their internal states is to vary the amino acid sequences of a given enzyme or of the subunits of an enzyme complex such as ATP synthase and electron transfer complexes, each containing a dozen or more subunits. This strategy of increasing the complexity of sequences may be forced upon cells because they cannot increase, beyond some threshold imposed by their physical dimensions, the variety of the spatial configurations of the components within their small volumes. In other words, it is impossible to pack in more than, say 10^9, enzyme particles into the volume of the yeast cell, about 10^{15} m^3, but the yeast cells can increase the variety of their internal states by increasing the variety of the amino acid sequences of their enzymes and enzyme complexes almost without limit, as a simple combinatorial calculus would show. For example, there would be at least $2^{100} = 10^{33}$ different kinds of 100-amino acid-residue polypeptides if each position can be occupied by one of at least two different amino acid residues. This line of thought led me to infer that there may be a new principle operating in living systems, here referred to as the "Maximum

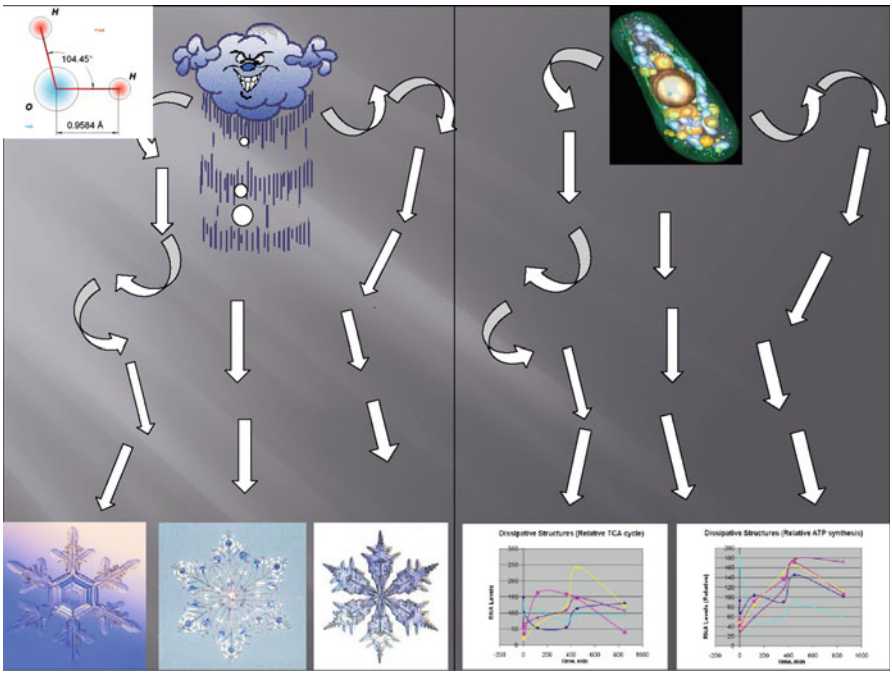

Fig. 5.3 Just as the shape of snowflakes reflect their trajectories through the atmosphere, so the different RNA trajectories measured from yeast cells are postulated to reflect the different microenvironmental conditions (see Fig. 12.28) under which RNA molecules are synthesized in the nucleus and degraded in the cytosol. Snowflakes are *equilibrium structures* or *equilibrons* whose sixfold symmetry are determined by the geometry of the water molecule, while RNA trajectories are *dissipative structures* or *dissipatons* (Sect. 3.1) whose shapes reflect the fact that cells are themselves *dissipative structures* maintaining their dynamic internal structures (including RNA trajectories) by continuously dissipating free energy. For the experimental details concerning the measurement of the RNA trajectories shown above, see Sect. 12.2 (Figure 5.3 was drawn by one of my undergraduate students, Ronak Shah, in April, 2009)

Variation Principle (MVP)" or the "Maximum Complexity Principle (MCP)," which states that:

> The variety of the internal states of living systems increases with evolutionary time. (5.11)

or

> The complexity of the internal states of living systems increase with evolutionary time. (5.12)

Statement (5.12) resembles that of the Second Law ("The entropy of an isolated system increases with time."), which may lead conflating MVP with the Second Law unless care is taken. MVP cannot be derived from the Second Law, because MVP embodies the evolutionary trajectories (or contingencies) of living systems (i.e., slowly changing environmental variations encountered by rapidly changing

short-lived organisms during evolution) just as the shapes of snowflakes (see Fig. 5.3) cannot be derived or predicted from the Second Law because these embody the trajectories (or a series of boundary conditions of Polanyi 1968) traversed by incipient snowflakes through the atmosphere, the information about which being lost to the past, except whatever is recorded in snowflakes.

Although all snowflakes exhibit a sixfold symmetry due to the unique structure of the water molecule (see the lower panels in Fig. 5.3), no two snowflakes look alike, and this phenomenon has now been well understood as the result of experimental works on artificial snowflakes produced in laboratories (see Sect. 15.1) (Libbrecht 2008): No two snowflakes look alike because no two snowflakes traverse the same trajectories from the atmosphere to the ground as they evolve from the incipient clusters of a few water molecules formed high up in the atmosphere to the final macroscopic snowflakes seen on the ground (see the left-hand panel in Fig. 5.3). Similarly, no two RNA trajectories measured from the yeast cell undergoing the glucose-galactose shift look exactly alike (see the bottom of the right-hand panel in Fig. 5.3), most likely because (1) no two RNA polymerases inside the nucleus and (2) no two RNA molecules in the cytosol experience identical microenvironments (see the RNA localizations in Drosophila embryios, Fig. 15.3). Consequently, no two RNA molecules are associated with identical rates of production (through transcription) and degradation (catalyzed by RNases or ribonucleases). In analogy to the sixfold symmetry exhibited by all snowflakes reflecting the geometry of the water molecule, all RNA trajectories share a common feature of being above the zero concentration levels reflecting the fact that the yeast cell is a dissipative structure, continuously dissipating free energy to maintain its dynamic internal structures, including RNA trajectories. Most of the discussions on complexity in the past several decades in the field of computer science and physics concern "passive complexity," which was taken over by biologists *apparently* without realizing that living systems may exhibit a totally new kind of complexity here dubbed "active complexity." The time- and space-dependent heterogeneous distributions of RNA molecules observed in developing *Drosophila* embryo (Fig. 15.1) provide a prototypical example of "active complexity," since depriving energy supply to the embryo would certainly abolish most of the heterogeneous RNA distributions.

5.2.4 *The Principle of Recursivity*

A "recursive definition," also called "inductive definition," defines something partly in terms of itself, that is, *recursively*. A clear example of this is the definition of the Fibonacci sequence:

$$\mathrm{F(n)} = \mathrm{F(n-1)} + \mathrm{F(n-2)} = 1, 1, 2, 3, 5, , \quad \text{.....} \quad (5.13)$$

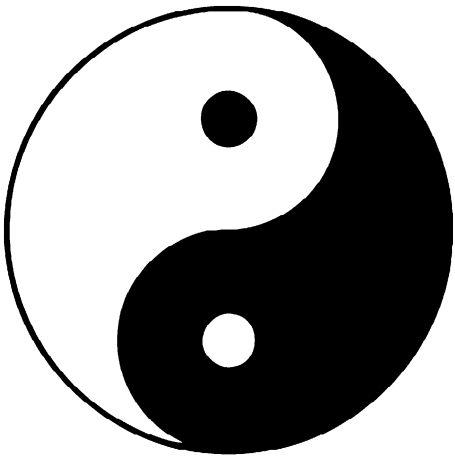

Fig. 5.4 The Yin-Yang symbol visualizing the concept of *embeddedness* (i.e., the *black dot* in the *white background*, and the *white dot* in the *black background*) and the *intertwining* (between the *white* and *black tear-drop* shapes) http://commons.wikimedia.org/wiki/File:Yin_yang.svg

where n is a natural number greater than or equal to 2. As can be seen, Eq. 5.13 defines the (n + 1)th Fibonacci number in terms of two previous Fibonacci numbers. A linguistic example of recursivity is provided by the acronym GNU whose definition implicates itself: "GNU is not Unix." A biological example of *recursivity* may be suggested to be the self-relication of the DNA double helix, since it implicates replicating the DNA double helix using the original DNA as the template: Self-replication of the DNA double helix is *self-referential*, or *recursive*. The growth of an organism from a fertilized egg cell can be viewed as recursive process in the sense that the fertilized egg serves as a template to form its daughter cell, the daughter cell in turn serving as the template for the production of the next generation cell, etc. The cell division is recursive or results from a series of recursive actions. On the basis of these analyses, it may be concluded that life itself is recursive.

Many physical, chemical, biological, engineering, and logical principles are mutually *inclusive* and *intertwined* in the sense that it is impossible to separate them completely. This principle is represented in the familiar Yin-Yang symbol of the Taoist philosophy (Fig. 5.4): The dot of the Yin (dark) is embedded in the sea of the Yang (light) and the dot of the Yang is embedded in the sea of the Yin. The embeddedness of the Yin in Yang (and vice versa) is reminiscent of the embeddedness of a sentence within a sentence in human language or the embeddedness of an algorithm within an algorithm in computer programming, both of which exemplify the *recursivity* (or the recursion and self-similarity) widely discussed in computer science (Hofstadter 1980).

The complementarity principle of Bohr seems to embody the principle of recursivity as the following argument shows. As is well known, Bohr in 1947 inscribed on his coat of arms the following motto:

Contraria sunt complementa. or (5.14)

Contraries are complementary. (5.15)

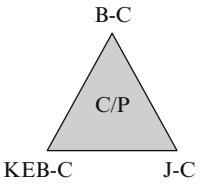

Fig. 5.5 A diagrammatic representation of the complementarity of complementarities, or the "recursive complementarity"

It is interesting to note that Statement 5.15 can be interpreted as either of the following two contrary statements, P and not-P:

All contraries are complementary. (5.16)

Not all contraries are complementary. (5.17)

Statement 5.17 is synonymous with 5.18:

Only some contraries are complementary. (5.18)

Statement 5.16 reflects the views of Kelso and EngstrØm (2006) and Barab (2010) who list over 100 so-called complementary pairs in their books. I favor Statements (5.17) and (5.18) based on the complementarian logic discussed in Sect. 2.3.3.

Since 5.16 and 5.17 are contraries, they must be COMPLEMENTARY to each other according to 5.15. That is, defining the relation between 5.16 and 5.17 as being complementary entails using Statement 5.15. This, I suggest, is an example of "recursive definition," similar to the definition of the Fibonacci sequence 5.13. To rationalize this conclusion, it appears necessary to recognize the three definitions of complementarities as shown below (where B, KE, and J stand for Bohr, Kelso and Engstrom, and Ji, respectively):

B-Complementarity (B-C) = Contraries are complementary. (5.19)

KEB-Complementarity (KEB-C) = All contraries are complementary. (5.20)

J-Complementarity (J-C) = Not all contraries are complementary. (5.21)

Since, depending on whether or not the complementarian logic is employed, the B-complementarity can give rise to either the KEB-or the J-complementarity, respectively, it appears logical to conclude that the KEB- and J-complementarities are themselves the complementary aspects of the B-complementarity. This idea can be represented diagrammatically as shown in Fig. 5.5.

After formulating the idea of the "recursivity of complementarity," I was curious to find out if anyone else had a similar idea. When I googled the quoted phrase, I was surprised to find that Sawada and Caley (1993) published a paper entitled "Complementarity: A Recursive Revision Appropriate to Human Science." This paper may be viewed as an indirect support for the conclusion depicted in Fig. 5.5. However, upon further scrutiny, there is an important difference between the perspective of Sawada and Caley (1993) and mine: Sawada and Caley believe that, in order to introduce the idea of recursivity to complementarity, Bohr's original complementarity must be revised (by taking the observer into account explicitly). In contrast, my view is that Bohr's original complementarity is

intrinsically recursive, due to its ability to generate two contrary statements, P and not-P, that is, Statements 5.16 and 5.17.

Finally, it should be pointed out that, if not all contraries are complementary (as I originally thought in contrast to the views of Kelso and EngstrØm (2006) and Barab (2010)), there must be at least one other relation operating between contraries. In fact, there may be at least three noncomplementary relations operating between contraries:

1. SUPPLEMENTARITY = C is the sum of A and B (e.g., energy and matter).
2. DUALITY = A and B are separate entities on an equal footing (e.g., Descartes' *res cogitans* and *res extensa*).
3. SYNONYMY = A and B are the same entity with two different labels or names (e.g., Substance and God in Spinoza's philosophy; the Tao and the Supreme Ultimate in Lao-Tzu's philosophy).

5.2.5 *Fuzzy Logic*

There are two kinds of logic – *classical* (also called Aristotelian, binary, or Boolean) *logic* where the truth value of a statement can only be either *crisp* yes (1) or no (0), and *multivalued logic* where the degree of truthfulness of a statement can be *vague or fuzzy* and assume three or more values (e.g., 0, 0.5, and 1). Fuzzy logic is a form of multivalued logic based on fuzzy set theory and deals with approximate and imprecise reasoning. In fuzzy set theory, the set membership values (i.e., the degree to which an object belongs to a given set) can range between 0 and 1 unlike in crisp set where the membership value is either 0 or 1. In fuzzy logic, the truth value of a statement can range continuously between 0 and 1. The concept of fuzziness in human reasoning can be traced back to Buddha, Lao-tze, Peirce, Russell, Lukasiewicz, Black, Wilkinson (1963), and others (Kosko 1993; McNeill and Freiberger 1993), but it was Lotfi Zadeh who axiomatized fuzzy logic in the mid-1960s (Zadeh 1965, 1995, 1996a).

Variables in mathematics usually take numerical values, but, in fuzzy logic, the non-numeric *linguistic variables* are often used to express rules and facts (Zadeh 1996b). Linguistic variables such as age (or temperature) can have a value such as young (warm) or old (cold). A typical example of how a linguistic variable is used in fuzzy logic is diagrammatically illustrated in Fig. 5.6.

5.2.6 *Fuzzy Logic and Bohr's Complementarity*

In Sect. 5.2.4, it was shown that the principle of Bohr's complementarity embodies the principle of recursivity as well, which may be seen as an example of the *intertwining among principles* as symbolized by the dark and white objects in the Yin-Yang diagram (Fig. 5.4). Bohr's complementarity exhibits fuzziness.

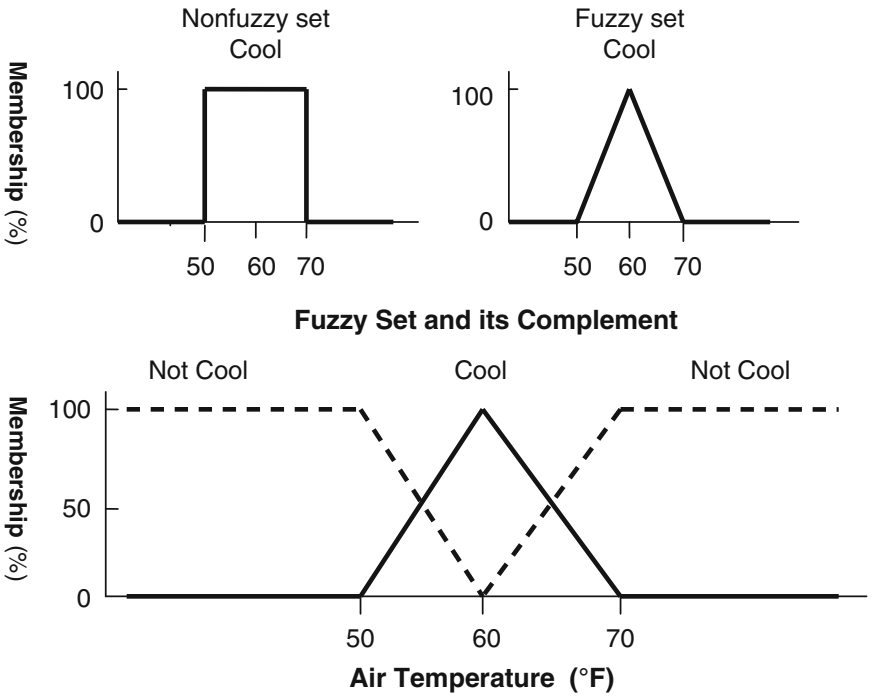

Fig. 5.6 Diagrammatic representations of *binary logic* and *fuzzy logic*. In standard logic, objects belong to a set completely (100%) or not at all (0 %) (see *top left*). In fuzzy logic, objects belong to a fuzzy set only to some degree (*top right*) and to the complement of the set to some other extent (*bottom*), the sum of the partial memberships always summing up to unity. For example, the air temperature of 50°F is 0% cool and 100% not cool; 55°F is 50% cool and 50% not cool; 60°F is 100% cool and 0% not cool; 65°F is 50% cool and 50% not cool; and 70°F is 0% cool and 100% not cool

According to fuzzy/vague/multivalence theorists, including Peirce, Russell, Black, Lukasiewicz, Zadeh, and Kosko (1993), words are fuzzy sets. The word "young" is an example of the fuzzy set. I am neither "young" (0) or old (1) but both young (to a degree of say 0.2) and old (to a degree of say 0.8). In other words I am both "young" and "not-young" (i.e., old) at the same time to certain degrees. Similarly, it can be suggested that the word "complementary" or "complementarity" is also a fuzzy set, since what is complementary to some scholars may not be complementary to others. For example, Kelso and EngstrØm list hundreds of complementary pairs in their book, *The Complementary Nature* (2006). Although their complementary pairs do satisfy Bohr's definition of complementarity, Statement (5.16), they certainly do not satisfy the definition of complementarity given in Sect. 2.3.3, which is based on three criteria of the complementarian logic:

1. *Exclusivity* (A and B are mutually exclusive)
2. *Essentiality* (A and B are both essential to account for C)
3. *Transcendentality* (C transcends the level where A and B have meanings)

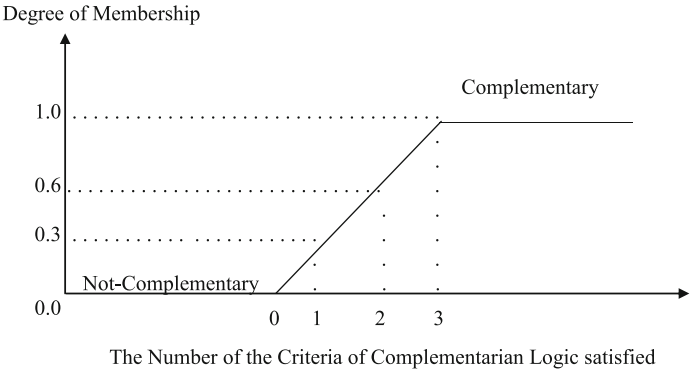

Fig. 5.7 The concept of complementarity as a fuzzy set

Table 5.3 Some examples of the complementary pairs of Kelso and EngstrØm whose degree of complementarity has been calculated on the basis of the three criteria of the complementarian logic discussed in Sect. 2.3.3 (These calculations are somewhat subjective)

Complementary pairs of Kelso and EngstrØm	Criteria of the complementarian logic			Degree of complementarity
	Exclusivity	Essentiality	Transcendentality	
Wave ~ particle	+	+	+	1.0
Information ~ energy	+	+	+	1.0
Energy ~ matter	−	+	−	0.3
Energy ~ time	+	+	−	0.6
Space ~ time	+	+	+	1.0
Mind ~ body	+	+	+	1.0
Object ~ subject	+	+	+	1.0
Abrupt ~ gradual	−	+	−	0.3
Even ~ odd	−	+	−	0.3
Perception ~ action	−	+	−	0.3
Vitalism ~ mechanism	+	−	+	0.6

Thus, some of the complementary pairs of Kelso and EngstrØm satisfy only one and some two of the above three criteria, and only a small number of them satisfy all of the three criteria. We may designate these complementary pairs as the 0-, 0.3-, 0.6-, and 1.0- complementary pairs, respectively, the fractions indicating the degree of membership to the complementary set (see the dotted lines in Fig. 5.7) calculated as the ratio of the number of the criteria satisfied over the total number of the criteria. Some examples of complementary pairs having different degrees of complementarities are listed in Table 5.3.

5.2.7 The Knowledge Uncertainty Principle (KUP)

The first line of the Taoist text, The Lao-Tze, states that

The Tao, once expressed, is no longer the permanent Tao. (5.22)

Table 5.4 The question and answer (QA) matrix. 1 = Yes; 0 = No

Answers	Binary questions				
	1	2	3	...	N
1	0	1	1	...	0
2	0	0	1	...	1
3	1	0	0	...	0
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
2^N	0.	0	0	...	1

which in Chinese can be written with just six characters that read in Korean thus:

Doh Gah Doh, Bee Sahng Doh.

We may refer to Statement 5.22 as the "Principle of Ineffability," probably one of the most important principles of the Taoist philosophy.

The purpose of this section is to formulate an "algebraic geometric" version of the Principle of Ineffability, which will be referred to as the "Knowledge Uncertainty Principle (KUP)" in analogy to the Heisenberg Uncertainty Principle (HUP) in quantum mechanics. For the purpose of the present discussion, I will differentiate "knowledge" from "information" as follows: *Knowledge* refers to actuality and *information* to potentiality, just as physicists differentiate between the probability wave function Ψ symbolizing "possible information" and its square Ψ^2 referring to measured information or probability (Herbert 1987; Morrison 1990). It may well turn out that KUP subsumes HUP as suggested by Kosko (1993). The KUP is based on the following considerations:

1. All human knowledge (including scientific knowledge) can be represented as sets of answers to N binary questions (i.e., questions with *yes* or *no* answers only), where N is the number of questions that defines the universe of discourse or the system plus its environment under observation/measurement. This resonates with Wheeler's "It from bit" thesis (1990) that *information* is as fundamental to physics as it is for computer science and that humans participate in producing all scientific information by acquiring the *apparatus-elicited answers* to yes-or-no questions as in *the game of 20 questions* (Sect. 4.15). Recently Frieden (2004) has claimed that all major scientific laws can be derived from maximizing the Fisher information of experimental data.
2. As shown in Table 5.4, each answer in (1) can be represented as a string of N 0's and 1's, for example (0, 1, 1, . . ., 0) for Answer #1, and (1, 0, 0, . . ., 0) for Answer #3, etc.
3. There will be a total of 2^N *N-bit strings* as the possible answers to a set of N questions (see the last row in Table 5.4).
4. The *N-bit strings* in Table 5.4 can be represented geometrically as the vertices of an N-dimensional hypercube (Kosko 1993, p. 30). An N-dimensional hypercube is a generalization of an ordinary cube which can be viewed as a

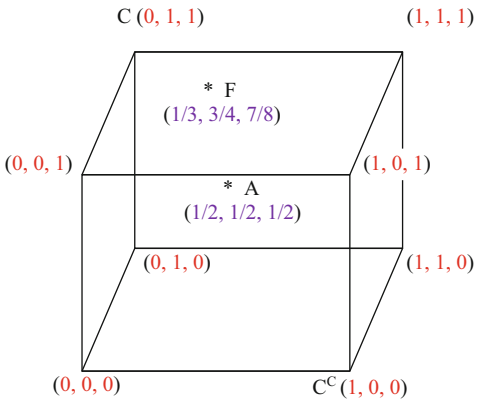

Fig. 5.8 A three-dimensional hypercube. One of the eight vertices is arbitrarily located at the origin (0, 0, 0) of the (x, y, i) coordinate system. Point A denotes the center of the hypercube. The closest vertex to point F is C(0, 1, 1), whose complement is vertex C^C(1, 0, 0)

three-dimensional hypercube (see Fig. 5.8). A square (e.g., one of the six aspects of a cube) can be treated as a two-dimensional hypercube. To generate a cube from a square, it is necessary only to move a square in a new direction (i.e., along the z-axis) perpendicular to the preexisting axes, the x- and y-axes in the case of a square. This operation can be repeated to generate an N-dimensional hypercube from an (N − 1)-dimensional one, where N can be any arbitrarily large number.

5. According to the principle of excluded middle, also called *the Aristotelian logic* or *crisp logic* (McNeill and Freiberger 1993; Kosko 1993), an answer is either true (1) or false (0), and no answer can have any truth values intermediate between 0 and 1. That is, no "crisp" answer can reside in the interior or on the edges of the hypercube, only on the vertices.
6. In contrast, the theory of fuzzy sets or the fuzzy logic (Zadeh 1965, 1995, 1996a, b; Kosko 1993) allows the truth value of an answer to be any positive number between 0 and 1, inclusive. For example, an answer with a truth value (i.e., the degree of membership to a set of true answers) of 3/4 is more true (1) than false (0); an answer with a truth value of 1/2 is both true and not-true at the same time, etc. The unit of fractional truth values is referred to as "fits" or "fuzzy units" (Kosko 1993).
7. Based on (5) and (6), we can conclude that "crisp" answers (expressed in bits) reside at the vertices or nodes of an N-dimensional hypercube, while fuzzy or vague answers (expressed in fits) reside in the interior or on the edges of the N-dimensional hypercube. For example, a fuzzy answer with a truth value of (1/2, 1/2, 1/2) will be found at the center of the cube (see point A in Fig. 5.8), whereas a fuzzy answer with truth value of (1/3, 3/4, 7/8) will be located at point F in Fig. 5.8.
8. It is postulated here that when the human mind is challenged with a set of N questions, it generates a fuzzy answer (say, F in Fig. 5.8) *unconsciously* (guided by intuition and previous experience), but, in order to communicate (or articulate) it to others, the human mind *consciously* search for the *nearest vertex*, say (0, 1, 1) in Fig. 5.8. Thus, *articulated* or *represented* crisp answers can be

assigned degrees of *truthfulness* or *certainty* measured as a ratio of two numbers, that is, D_1/D_2, where D_1 is the distance between the fuzzy answer (located at coordinate F) in the N-dimensional hypercube and its nearest vertex located at C and D_2 is the distance between F and the vertex, C^C, that is irreconcilably opposite to C. (C^C is called the *complement* of C.) The bit values of crisp C^C are obtained by subtracting the corresponding bit values of C from 1. For example, the complement of C(1, 0, 1) is C^C (1-1, 1-0, 1-1), or C^C (0, 1, 0). The distance, D_{AB}, between the two points, A ($a_1, a_2, a_3, \ldots, a_k$) and B ($b_1, b_2, b_3, \ldots, b_k$), can be calculated using the Pythagorean theorem:

$$D_{AB} = \left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2 + ..., + (a_k - b_k)^2\right]^{1/2} \quad (5.23)$$

Applying Eq. 5.23 to points C and F, and C^C and F in Fig. 5.8, the ratio of D_1 over D_2 can be calculated, which Kosko referred to as *fuzzy entropy* (Kosko 1993, pp. 126–135), one of many fuzzy entropies defined in the literature. For convenience, we will refer this ratio as the *Kosko entropy*, denoted by S_K, in recognition of Kosko's contribution to the science of fuzzy logic. S_K now joins the list of other well-known *entropies* in physics and mathematics – the Clausius (which may be denoted as S_C), Boltzmann (as S_B), Shannon (as S_S), Tsalis entropies (as S_T), etc. The Kosko entropy of a fuzzy answer is then given by:

$$S_K = D_{CF}/D_{FC}{}^c \quad (5.24)$$

where D_{CF} is the distance between crisp point C and fuzzy point F and $D_{FC}{}^c$ is the distance between crisp point C^C and fuzzy point F. Formally, Eq. 5.24 constrains the numerical values of S_K to the range between 0 and 1:

$$1 \geq S_K \geq 0 \quad (5.25)$$

However, both the Principle of Ineffability, Statement 5.22, and the Einstein's Uncertainty Thesis, Statement 5.38 (see below), strongly indicate that S_K cannot be equal to 1 or to 0, leading to Inequality 2.26:

$$1 > S_K > 0 \quad (5.26)$$

According to Inequality 5.26, the maximum value of S_K is less than 1 and its minimum value is greater than 0. If we designate the minimum uncertainty that no human knowledge can avoid with *u* (from uncertainty) in analogy to the Planck constant *h* below which no *action* (i.e., the energy integrated over time) can exist, Inequality 5.26 can be rewritten as:

$$1 > S_K \geq u \quad (5.27)$$

where u is a positive number whose numerical values probably depend on the measurement system involved.

9. The Kosko entropy of fuzzy answer F in Eq. 5.28 is given by:

$$\begin{aligned} S_K(F) &= \left[(0-1/3)^2+(1-3/4)^2+(1-7/8)^2\right]^{1/2} / \left[(1-1/3)^2+(0-3/4)^2 \right. \\ &\qquad \left. +(0-7/8)^2\right]^{1/2} \\ &= \left[(2/3)^2+(1/4)^2+(1/8)^2\right]^{1/2} / \left[(2/3)^2+(-3/4)^2+(-7/8)^2\right]^{1/2} \\ &= [4/9+1/16+1/64]^{1/2} / [4/9+9/16+49/64]^{1/2} \\ &= [0.4444+0.0625+0.016] / [0.4444+0.5625+0.7656] \\ &= 0.5229/1.7725 \\ &= 0.2950 \end{aligned} \tag{5.28}$$

10. As evident in (8) and (9), it is possible to calculate the numerical value of the *Kosko entropy* of any fuzzy answer F, $S_K(F)$. But what is the meaning of $S_K(F)$? It is here suggested that the Kosko entropy, S_K, of fuzzy answer F is a *quantitative measure of the uncertainty* that F is C (or C is F, for that matter). By multiplying $S_K(F)$ with 100, we can express this uncertainty in the unit of %:

$$S_K(F) \times 100 = \text{ The percent uncertainty that F is C (or C is F)} \tag{5.29}$$

Applying Eq. 5.29 to the result in Eq. 5.28, we can conclude that

It is 29.5% certain that fuzzy answer located at (1/3, 3/4, 7/8) is equivalent to (and hence can be represented by) the crisp answer located at (0, 1, 1). (5.30)

If we assume that

All crisp answers are approximations of their closest fuzzy answers (5.31)

we can reexpress Statement 5.30 as follows:

The uncertainty of crisp answer C (0,1,1) is (100 - 29.5) = 70.5 %. (5.32)

11. Statements 5.31 and 5.32 would gain a strong support if we can associate the interior of the N-dimensional hypercube defined in Table 5.4 with *reality* or the source of the apparatus-elicited answers of Wheeler (1990) and its vertices with possible, theoretical, or represented answers. The apparatus-elicited answers may have two aspects – the "registered" aspect when artificial apparatuses are employed and "experienced" aspect when living systems are involved as measuring agents. Frieden (2004) associates the former with *Fisher information* (I) and the latter with what he refers to as "bound information" (J), that is, the algorithmic information needed to characterize the "source effects" that underlie registered data or crisp answers. In the case of Frieden (2004), it seems clear that the registered answers (carrying Fisher information, I) belong to the vertices of the N-dimensional hypercube and the "experienced" answers or

"bound information," J, belong to the interior of the N-dimensional hypercube. If these identifications are correct, the following generalizations would follow:

All crisp answers are uncertain. (5.33)

All crisp answers have non-zero Kosko entropies. (5.34)

No crisp answers can be complete. (5.35)

Reality cannot be completely represented. (5.36)

The ultimate reality is ineffable. (5.37)

12. Einstein stated (cited, e.g., in Kosko 1993, p. 29) that

As far as the laws of mathematics refer to reality, they are not certain; and as far as they are certain, they do not refer to reality. (5.38)

Since Statement 5.38 is very often cited by physicists and seems to embody truth, it deserves to be given a name. I here take the liberty of referring to Statement 5.38 as the *Einstein's Uncertainty Thesis* (EUT).

EUT can be accommodated by the Knowledge Uncertainty Principle (KUP) as expressed in Statements 5.33–5.38, if *we identify the volume or the interior of the N-dimensional hypercube with "reality"* as already alluded to in (11) *and its surface (*i.e.*, some of its vertices) as the "laws of mathematics"*. Again, we may locate crisp articulations of all sorts (including mathematical laws and logical deductions) on the vertices of the N-dimensional hypercube and the "ineffable reality" in the interior or on the edges of the hypercube. If this interpretation is correct, at least for some universes of discourse, we may have here a possible *algebraic-geometric (or geometro-algebraic) rationale* for referring to the *N-dimensional hypercube* defined in Table 5.4 as the "reality hypercube (RH)" or as "a N-dimensional geometric representation of reality," and Inequality 5.27 and Statement 5.38 as the keystones of a new theory that may be called the "Algebraic Geometric Theory of Reality (AGTR)." It is hoped that RH and AGTR will find useful applications in all fields of inquiries where uncertainties play an important role, including not only physics (see (13) below) but also biology, cognitive neuroscience, risk assessment, pharmacology and medicine (see Chap. 20), epistemology, and philosophy, by providing an objective and visual theoretical framework for reasoning.

13. The wave-particle duality of light (see Sect. 2.3.1) served as a model of the complementarity pair in the construction of the philosophy of complementarity by N. Bohr in the mid-1920s (Plotnitsky 2006; Bacciagaluppi and Valenti 2009), although it was later replaced with the more general "kinematics-dynamics complementarity pair" (Murdoch 1987). Assuming that the wave-particle duality of light embodies an uncertainty principle (in addition to a complementarity principle to a certain degree), it will be analyzed based on the KUP, Eq. 5.29. The analysis involves the following steps:

    1. *Classical concepts*: The concepts of *waves* and *particles* have been well established in human language, having developed over thousands of years as a means to facilitate communication among humans about physical processes.

Table 5.5 The QA matrix for the wave-particle duality of light. N = the number of questions

Possible answers (N^2)	Binary questions (N = 2)	
	1	2
[1]	0	0
[2]	0	1
[3]	1	0
[4]	1	1

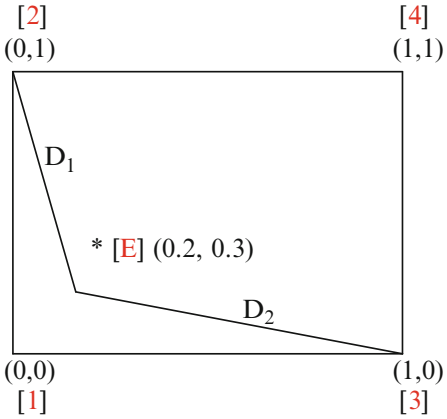

Fig. 5.9 The *N*-dimensional hypercube (where $N = 2$) representation of the QA matrix concerning the wave-particle duality of light

2. *Observations*: Light has been found to exhibit the dual properties of both waves and particles, depending on the measuring apparatus employed, which cannot be readily combined into one picture.
3. *Binary questions*: The paradoxical observation in (2) can be summarized in the form of two binary questions.

   Is light wave ? Yes = 1, No = 0
   Is light a particle? Yes = 1, No = 0

4. *The QA matrix*: The binary questions (Qs) have a finite number of possible answers (As) suggested by existing knowledge which can be represented as a QA matrix defined in (**2**) (Table 5.5).
5. *N-Dimensional hypercube*: The QA matrix can be transformed into an N-dimensional hypercube (Fig. 5.9), where N is the number of the binary questions related to the wave-particle duality of light. That is, the QA matrix and its associated N-dimensional hypercube are *isomorphic* in the sense that they obey the same set of common logical principles, including the principle of fuzzy logic (Kosko 1993).
6. *Apparatus-elicited answers (AEAs)*: To choose among the theoretically possible answers, experiments are designed and carried out to register AEAs, that is, the answers provided by nature (including the observer which, with Bohr, is thought to comprise a part of the experimental

arrangement and the registering device). Three AEAs are indicated in Fig. 5.9, two of which are well established and the third is hypothetical:

Photoelectric experiment = [2]
Two-slit experiment = [3]
A novel experiment = [E] (0.2, 0.3).

7. Kosko entropy, S_K: The Kosko entropy, defined in (**8**) above, of the fuzzy answer [E] can be calculated from the coordinates given in the two-dimensional hypercube, Fig. 5.9:

$$\begin{aligned} S_K(E) &= D_1/D_2 \\ &= \left\{(0-0.2)^2+(1-0.3)^2\right\}^{1/2} / \left\{(1-0.2)^2+(00.3)^2\right\}^{1/2} \\ &= \left\{4\times10^{-2}+49\times10^{-2}\right\}^{1/2} / \left\{64\times10^{-2}+9\times10^{-2}\right\}^{1/2} \\ &= (0.53^{1/2})/(0.73^{1/2}) \\ &= 0.726^{1/2} = 0.852 \end{aligned} \tag{5.39}$$

8. *Uncertainties of crisp (or nonfuzzy) statements*: Applying Eq. 5.29 to crisp answers [2] and [3], the associated uncertainties, defined in (**10**), can be calculated as:

$$S_K([2]) \times 100 = 0.85 \times 100 = 85\% \tag{5.40}$$

$$S_K([3]) \times 100 = (1-0.85) \times 100 = 15\% \tag{5.41}$$

Equations 5.40 and 5.41 indicate that crisp answers [2] and [3] are 85% and 15% uncertain, respectively, relative to the apparatus-elicited answer [E].

Applying Eq. 5.29 to the Airy experiment (AE) (Herbert 1987, pp. 62–63), two calculations are possible:

The Airy pattern is an experimental evidence that light is both waves and particles, that is, crisp answer [4] (1, 1), supporting the de Broglie equation, $\lambda = h/p$:

$$S_K([4]) = 0 \tag{5.42}$$

$$\text{Uncertainty } ([4]) = 0\% \tag{5.43}$$

The Airy pattern demonstrates that light is particles when observed over a short time period and waves when observed over a long period of time:

$$\begin{aligned} S_K(AE) &= 1, \text{ since } D_1 = D_2, \text{ and Uncertainty } = S_K(AE) \times 100 \\ &= 1 \times 100 = 100\% \end{aligned} \tag{5.44}$$

Equation 5.44 indicates that the Airy experimental result is 100% uncertain as to whether light is wave or a particle. In other words, the crisp answers [2], [3], and [4] are all 100% uncertain with respect to the question whether they are true relative to the Airy experimental data.

14. In Sect. 2.3.4, the logical relation between the HUP and Bohr's Complementarity Principle (BCP) was substantially clarified based on a geometric argument which may be viewed as a species of the so-called *table method* (Ji 1991, pp. 8–13). The result is that

The HUP presupposes Bohr's complementarity principle (BCP) and BCP can give rise to uncertainty principles including HUP. (5.45)

Statement 5.45 may be referred to as the *non-identity of the uncertainty and complementarity principles* (NUCP).

5.2.8 The Universal Uncertainty Principle

Although the quantitative form of the uncertainty principle was discovered by Heisenberg in physics in 1926 (Lindley 2008), the essential notion behind the uncertainty principle appears to be more general. Theoretical support for such a possibility can be found in the so-called "spectral area code" (Herbert 1987, pp. 87–89),

$$\Delta W \times \Delta M > 1 \tag{5.46}$$

where ΔW and ΔM are the spectral widths (or bandwidths) of conjugate waves W and M, respectively. A spectral width is defined as the number of waveforms into which a wave can be decomposed. The size of a bandwidth is inversely related to the closeness with which a wave resembles its component waveforms. Inequality 5.46 is called the "spectral area code," since the product of two numbers (i.e., bandwidths ΔM and ΔW) can be viewed as an area (*vis-à-vis* lines or volumes). When wave X is analyzed with the W prism (or software), a particular bandwidth ΔW of the output W waveforms is obtained, which is an inverse measure of how closely the input wave X resembles the members of the W waveform family. Similarly, when X is analyzed with the M prism, another bandwidth ΔM is obtained, which is an inverse measure of how closely the input wave X resembles the members of the M waveform family. Since W and M are mutual conjugates (i.e., polar opposites), it is impossible for wave X to resemble W and M both. Hence, there exists some restriction on how small these two spectral widths can get for the same input wave. Such a restriction is given by Eq. 5.46.

To relate the *spectral area* code to the Universal Uncertainty Principle, it is necessary to make two additional assumptions: (1) All human knowledge can be quantitatively expressed in terms of waves (each wave having three characteristic parameters, amplitude, frequency, and phase) and (2) The *Fourier theorem* and its

generalization known as the *synthesizer theorem* (Herbert 1987, pp. 82–84) can be used to decompose any wave, either physical or nonphysical, into a sum of finite set of component waveforms. The difference between the "physical wave" such as water waves and "nonphysical wave" such as quantum wave is this: The square of the amplitude of a *physical wave* is proportional to energy, whereas the square of the amplitude of *nonphysical wave* is proportional to the *probability* of the occurrence of some event.

Herbert (1987, pp. 87–89) provides an example of the spectral area code in action, namely, the complementary abilities of analog and digital synthesis techniques. An analog synthesizer can construct a sound wave X out of a range of sine waves with different frequencies k. Each wave X, depending on its shape, requires a certain spectral width Δk of sine waveforms for its analog synthesis. The sine wave's conjugate waveform is the impulse wave, which is the basis of digital music synthesis. A digital synthesizer forms a wave X out of a range of impulse waves with different values of position x. Each wave requires a certain spectral width Δx of impulse waves for its digital synthesis. According to the spectral area code, Eq. 5.46, the product of the spectral bandwidth of sine waves ant that of impulse waves must satisfy the *spectral area code*, leading to:

$$\Delta k \times \Delta x > 1 \tag{5.47}$$

Short musical sounds (such as from a triangle or a woodblock) have a narrow impulse spectrum. According to Inequality 5.47, to analog-synthesize such crisp sounds (i.e., with small Δx) requires a large range of sine waves (i.e., with large Δk). To synthesize an infinitely short sound, that is, the impulse wave itself, requires all possible since waveforms. In contrast, musical sounds that are nearly pure tones such as from a flute, an organ, or a tuning fork have a narrow sine spectrum. To digitally synthesize such pure tones, the spectral area code requires a large range of impulse waves. The spectral area code informs us that *analog* and *digital* music synthesizers are *complementary*: One is good for synthesizing long waveshapes, the other for short ones. Analogously, it may be stated that the *photoelectric effect devices* and *optical interference devices* are complementary to each other: One is good for measuring the particle nature of light, the other is good for measuring the wave nature of light. Thus, it may be concluded that the complementarity principle of Bohr is a natural consequence of the *spectral area code*, Inequality 5.46.

These considerations based on the *synthesizer theorem* and the *spectral area code* provide theoretical support for the notion that there are at least three kinds of uncertainty principles in nature – (1) the *Heisenberg Uncertainty Principle* in *physics* (see Inequalities 2.38 and 2.39), (2) the *Cellular Uncertainty Principle* in *cell biology* formulated in the late 1990s based on the molecular model of the cell known as the Bhopalator (Ji 1985a, b, 1990, 1991, pp. 119–122) as explained in Fig. 5.10 below, and (3) the *Knowledge Uncertainty Principle* in *philosophy* (see Sect. 5.2.7). One question that naturally arises is "What, if any, is the connection among these three uncertainty principles?" Is the HUP perhaps ultimately

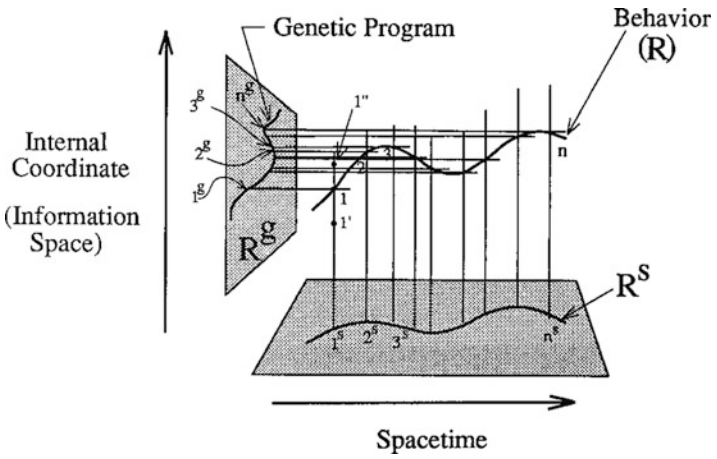

Fig. 5.10 The cellular uncertainty principle derived from living processes represented in the five-dimensional space, four dimensions of spacetime and one additional dimension for biological information (Reproduced from Ji 1991, p. 121)

responsible for the other two uncertainty principles? I do not think so. Rather I think it is more likely that these three uncertainty principles are *mutually exclusive* and constitute special cases of a more general principle, here termed the *Universal Uncertainty Principle* that operates in the Universe, leading to the following assertion:

> There exists a principle in this universe that manifests itself as the Heisenberg Uncertainty Principle, the Cellular Uncertainty Principle, or the Knowledge Uncertainty Principle, depending on whether the system under consideration is the *quantum object*, *the living cell*, or *the human brain*. (5.48)

Statement (5.48) will be referred to as the *Postulate of the Universal Uncertainty Principle* (PUUP). As already alluded to above, the ultimate basis for the validity of PUUP may be found in the *synthesizer theorem* and the *spectral area code* (Herbert 1987).

One utility of PUUP may be its ability to protect philosophers, literary critics, anthropologists, journalists, artists, and others from being criticized for invoking *Heisenberg's Uncertainty Principle* to describe "uncertain" situations/scenarios encountered in their own fields of specializations. For example, Lindley (2008), in his otherwise insightful and informative book on the history of the uncertainty principle in physics, chastised one editorialist who invoked the Heisenberg Uncertainty Principle by claiming that "the more precisely the media measures individual events in a war, the more blurry the warfare appears to the observer." Had the editorialist under attack invoked the PUUP instead of Heisenberg's uncertainty principle, he would have avoided Lindley's criticism on a sound logical basis.

The Cellular Uncertainty Principle (CUP) mentioned above is derived as follows (Ji 1991, pp. 118–122). It is assumed that the complete characterization of life

entails specifying the behavior of the smallest unit of life, the cell. The cell behavior is depicted as a curvy line denoted as **R** (from "river," the symbol of life) in Fig. 5.10. The genetic program responsible for the cell behavior is indicated as the projection $\mathbf{R}^{\mathbf{g}}$ of **R** onto the internal coordinate (or genetic information) space (see the vertical plane on the left in Fig. 5.10). The projection of **R** onto the spacetime plane produces its spacetime trajectory denoted as $\mathbf{R}^{\mathbf{s}}$.

The trajectory **R** is postulated to be composed of N sub-trajectories called "streams," where N is the number of biopolymers inside the cell. Each stream represents the behavior of one biopolymer inside the cell. The uncertainty about the behavior about the cell cannot be less than the uncertainty about the behavior of one of the N biopolymers. The uncertainty about the behavior of a biopolymer inside the cell can be estimated as follows:

1. There is a finite amount of uncertainty that is associated with the determination of the Gibbs free energy change underlying a given intracellular process catalyzed by a biopolymer. This uncertainty is designated as ΔG. Since driving any net biological process necessitates dissipating Gibbs free energy at least as large as thermal energies, kT, it would follow that the smallest uncertainty about the measurement of the Gibbs free energy change attending a biopolymer-catalyzed process inside the cell can be estimated to be

$$\Delta G \geq \text{kT} \quad \text{kcal/mol} \tag{5.49}$$

2. Due to ΔG, the cross section of the behavior trajectory **R** of the biopolymer possesses a finite size. This leads to an uncertainty about the internal coordinate (i.e., the genetic information) of the biopolymer, since there are at least two internal coordinates that can be accommodated within the cross section of **R** (see 1, 1', and 1" and their projections, not shown, onto the information space). Therefore, the uncertainty concerning the genetic information associated with the biopolymer behavior is at least one bit:

$$\Delta I \geq 1 \quad \text{bit} \tag{5.50}$$

3. Inequalities 5.49 and 5.50 can be combined by multiplication to obtain what was referred to as *the Cellular Uncertainty Principle* in (Ji 1991, pp. 119–122):

$$(\Delta G)(\Delta I) \geq \text{kT} \quad \text{bit kcal/mol} \tag{5.51}$$

The three uncertainty principles discussed above are given in the first rows of Tables 5.6, 5.7, and 5.8, the first two of which are the modified forms of Tables 2.9 and 2.10 in Sect. 2.3. The two forms of the HUP are reproduced in the first row of Table 5.6, that is, Inequalities 2.38 and 2.39. These inequalities are displayed in the table as the *horizontal* and *vertical* margins, respectively. As pointed out in Sect. 2.3.5, the *uncertainty relations are located on the margins of the table and the complementary relations such as the kinematics-dynamics duality are located in the diagonal boxes (or the interior) of the table*, suggesting that the uncertainty

Table 5.6 The relation between the *uncertainty principles* and *complementary relations* in physics, all thought to result from the numerical values of the critical parameters, h and c

Physics $\Delta q \cdot \Delta p \geq h/2\pi$ . . . . . (2.38) $\Delta t \cdot \Delta E \geq h/2\pi$ . . . . . (2.39)		
h, c	Position (q)	Momentum (p)
Time (t)	1. Wave 2. Spacetime 3. Kinematics 4. Globality 5. Continuity 6. Group (or superposition)	
Energy (E)		1. Particle 2. Momenergy 3. Dynamics 4. Locality 5. Discontinuity 6. Individuality

Table 5.7 The postulated relation between the *cellular uncertainty principle* and the *liformation-mattergy complementarity* in biology

Biology $\Delta G \cdot \Delta I \geq kT$ . . . . . (5.51) $\Delta L \cdot \Delta m \geq kT$ . . . . . (5.52)		
kT	Life (L)	Matter (m)
Information (I)	1. Wave 2. Kinematics 3. Liformation 4. Structure	
Energy (E)		1. Particle 2. Dynamics 3. Mattergy 4. Function

principles and the complementary principles belong to two different logical classes in agreement with Murdoch (1987, p. 67). Although the wave-particle duality is widely regarded as the empirical basis for Bohr's complementarity principle, this view is considered invalid since Bohr's complementarity principle has been found to be upheld in the so-called which-way experiments even when the HUP is not applicable (Englert et al. 1994). Therefore, the wave-particle duality must be viewed as valid only under some specified experimental situations such as the gamma-ray microscopic experiment (Murdoch 1987, p. 50) and not universally. Similarly, all of the *complementary pairs* listed in the diagonal boxes of Table 5.6 may hold true only under appropriate experimental or observational situations and not universally.

Table 5.8 The extension of the principles of uncertainty and complementarity from physics and biology to philosophy. M = mind, B = body, S = soul, and P = personality. The symbol u denotes the postulated minimum uncertainty below which no human knowledge can reach

Philosophy		
$\Delta M \cdot \Delta B \geq u$ . . . . . (5.53)		
$\Delta S \cdot \Delta P \geq u$ . . . . . (5.54)		
u	Soul (S)	Personality (P)
Mind (M)	1. Wave	
	2. Liformation	
	3. Fuzzy logic	
Body (B)		1. Particle
		2. Mattergy
		3. Crisp logic

If the Symmetry Principle of Biology and Physics (SPBP) described in Table 2.5 is valid, it may be predicted that the relation between the *uncertainty principle* and the *complementarity principle* as depicted in Table 5.6 may have a biological counterpart. One such possibility is shown in Table 5.7, which is almost identical with Table 2.7, except for the inclusion of the postulated uncertainty relations, Inequalities 5.51 and 5.52. In Inequality 5.51, which was derived on the basis of a geometric argument (Ji 1991, pp. 120–122), ΔG is the uncertainty about the measurement of the Gibbs free energy change accompanying an intracellular process at temperature T, ΔI is "the uncertainty about the biological significance of the cellular processes under study, for example, the uncertainty about the 'fitness' value of the cellular processes involved" (Ji 1991, p. 120), and k is the Boltzmann constant. It is assumed that the critical parameter in biology is the *thermal energy per degree of freedom*, that is, kT, which is thought to be analogous to h (see Statement (4.36)). Again, in analogy to the canonical conjugates in physics (i.e., the q–p and t–E pairs), it is assumed in Table 5.7 that the canonical conjugates in biology are information-life (I-L) and energy and matter (E–m) pairs. If this conjecture is valid, we can derive another uncertainty relation in biology, namely, $\Delta L \cdot \Delta m \geq kT$, where ΔL is the uncertainty about whether the object under investigation is alive or death, and Δm is the uncertainty about the material constitution or configuration of the living object under consideration.

Finally, if the complementarity principle revealed in *physics* and *biology* can be extended to philosophy as envisioned by Bohr (1934) and myself (Ji 1993, 1995, 2004b), it should be possible to construct a table similar to Tables 5.6 and 5.7 that applies to philosophy. One possibility is shown in Table 5.8. Just as the extension of the uncertainty and complementarity principles from physics to biology entailed recognizing a new complementary pair (i.e., *liformation* vs *mattergy* in Table 5.7), so it is postulated here that there exists a novel kind of complementarity observable at the philosophical level, and that complementary pair is here suggested to be the *crisp* versus *fuzzy logics* (see the diagonal boxes in Table 5.8).

Associated with the crisp versus fuzzy logics *complementarity* are suggested to be *two uncertainty relations,* Inequalities 5.53 and (5.54), where ΔM is the

uncertainty associated with defining the mind, ΔB is the uncertainty associated with defining the body, ΔS is the uncertainty about what constitutes soul, ΔP is the uncertainty about what determines one's personality, and u expressed in fits, the fuzzy units (Kosko 1993), is thought to be the minimum amount of uncertainty that necessarily accompanies all human knowledge and communication. "Knowledge" is here defined simply as the ability to answer questions, and the amount of the knowledge a person possess can be measured by the number of questions that can be answered by a person possessing the knowledge. Inequality (5.53) may be interpreted as stating that the more precisely one determines what mind is in nonmaterial terms, the less precisely can one define the role of the body in the phenomenon of mind. Similarly, the more precisely one determines what the body is from the biochemical and physiological perspectives, the less precisely can one determine what mind is from the psychological perspective. This complementarity-based view of mind appears to be consistent with the hologram-based theory of mind proposed by Pribram (2010). Inequality (5.54) may be interpreted to mean that the more precisely one determines what soul is, the less precisely can one determine what personality is. The more precisely one can determine what personality is, the less precisely can one determine what soul is. This conjecture was motivated by the statement made by a Japanese theologian in Tokyo in the mid-1990s to the effect that "it is relatively easy to know whether a human being has a personality but it is very difficult to know whether he or she has a soul."

The three kinds of the uncertainty principles described in Tables 5.6, 5.7, and 5.8 are recapitulated in Table 5.9, along with their associated complementarity principles.

Several features emerge from Table 5.9:

1. Although the first mathematical expression of the uncertainty principle was discovered in physics by Heisenberg in 1926 (Lindley 2008), the qualitative concept of uncertainty in human knowledge is much older, going back to Lao-tse, for example (see Statement 5.22). The mathematical expressions for the uncertainty principle applicable to cell biology and psychology/philosophy are formulated for the first time in this book (see the first and second rows in Table 5.9).
2. The intense discussions on Heisenberg's uncertainty principle in physics and philosophy of science during the past seven decades (Murdoch 1987; Plotnitsky 2006; Lindley 2008) have created the impression that there exists only one overarching principle of uncertainty, namely, that of Heisenberg. But Table 5.9 suggests that there exists a multiplicity of uncertainty principles, each reflecting specific mechanisms of interactions among the components of the system under consideration, from the atom to the cell to the human brain. Just as the complementarity principle advocated by Bohr on the basis of quantum mechanical findings was postulated to have counterparts in fields other than physics (Bohr 1933, 1958; Pais 1991; Ji 1991, 1993, 1995; Kelso and EngstrØm 2006; Barab 2010), so it appears that the uncertainty principle first recognized in quantum mechanics has counterparts in fields other than physics.

Table 5.9 The uncertainty principles in physics, biology, and philosophy

	Uncertainty principle		
	Heisenberg	Cellular	Knowledge
1. System (volume, m^3)	Atom (10^{-30})	Cell (10^{-15})	Brain (1)
2. Uncertainty inequality (minimum Uncertainty)	$\Delta q \cdot \Delta p \geq h/2\pi$ $\Delta t \cdot \Delta E \geq h/2\pi$ ($\sim 10^{-27}$ erg s)	$\Delta G \cdot \Delta I \geq \gamma$[a] ($\sim 10^{-14}$ erg)	$\Delta X \cdot \Delta Y \geq u$[b] ($\sim 10^{-2}$)
3. Complementary pairs	Wave versus particle	Linformation versus mattergy	Fuzzy versus crisp (*Kosko* 1993)
	Kinematics versus dynamics	Diachronicity versus synchronicity[c]	Continuity versus discontinuity
	Measuring instruments A versus B	Structure versus process	Local versus global
			Classical versus nonclassical epistemology (*Plotnitsky* 2006)
4. Key principles	Principle of the quantum (or the quantization of action, i.e., energy × time)	Principle of self-organization	Principle of ineffability (Statement 5.22)
		Principle of the conformon (or the quantization of biological action) (*Ji* 2000)	Einstein's uncertainty thesis (Statement 5.38)
			Principle of minimum uncertainty: i.e., $u > 0$ (see inequality [5.27])
5. Quantum (alternative names)	Action = h (**quons**, **ergons**[d])	Life = γ (conformons, gnergons[e])	Knowledge = u[f] (gnons[g])
6. Concerned with (discrete units)	Energy (ergons)	Gnergy (gnergons)	Information (gnons)
7. Field of study	Physics	Biology	Philosophy/psychology

[a] The minimum size of the conformon postulated to be kT or 4.127×10^{-14} ergs (or 0.594 kcal/mol) (Ji 1991, p. 32)

[b] To maintain the symmetry of the table, it is postulated that there exist one or more uncertainty pairs denoted as X and Y such that increasing the precision of describing X is possible if and only if the precision of describing Y is reduced proportionately so that their product is always greater than some minimum uncertainty symbolized by u. One example of X and Y may be suggested to be *natural language* and *mathematics*. The minimum uncertainty of human knowledge, u, may be represented in terms of the Kosko entropy, S_K, that cannot be reduced to zero nor exceeds 1. The numerical value of *u* has been conjectured to be about 10^{-2}, which is about 12 orders of magnitude greater than *kT*, the minimum size of the cellular uncertainty, and about 25 orders of magnitude greater than *h*, the minimum size of quantum mechanical uncertainty

[c] Cells are evolving systems whose current properties and processes have been selected by evolution and hence cannot be completely understood without taking into account their past history as recorded in their structures, for example, DNA. In other words, cells can be described in two complementary ways – via the *diachronic* and the *synchronic* approaches (see Sect. 4.5)

[d] The energetic aspect of gnergy, the complementary union of information and energy (Sect. 2.3.2)

[e] The discrete unit of gnergy (Sect. 2.3.2)

[f] The symbol u refers to the *minimum uncertainty* in human knowledge which is equivalent to the *maximum human knowledge,* because it takes a maximum amount of information to minimize uncertainty

[g] The informational aspect of gnergy (Ji 1991, pp. 1, 152 and 160)

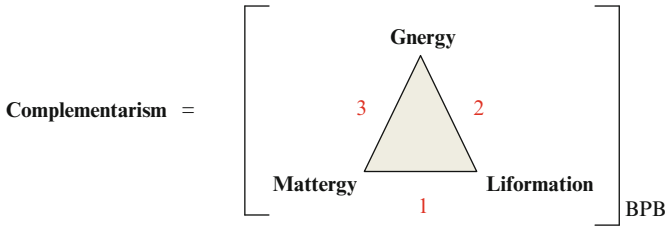

Fig. 5.11 A three-node network representation of *complementarism*

3. The uncertainty inequality differs from systems to systems as evident in the second row. The numerical value of the minimum uncertainty associated with a given system appears to increase approximately linearly with its material volume (compare the first two rows).
4. The complementarity pairs associated with their associated uncertainty inequalities also vary depending on systems (see the second and third rows).
5. The key principles underlying each uncertainty inequality and its associated complementarity pair depend on systems, the principle of self-organization for cells (discussed in Sect. 3.1) being a prime example (see the fourth row).
6. Just as the *action* is quantized in physics, so it is proposed here that *life* and *knowledge* are quantized in cell biology and psychology/philosophy (see the fifth row).
7. Somewhat simplifying, physics may be viewed as the study of *energy* (or ergons), cell biology as the study of *gnergy*, and philosophy/psychology as the study of *information* (or gnons) (see the sixth row).
8. One of the most significant conclusions suggested by Table 5.9 is that there is no overarching uncertainty principle nor is there an associated complementarity principle but these principles are all *system-dependent*, giving rise to a multiplicity of uncertainty principles and complementarity principles:

   Uncertainty principles and complementarity principles are system-dependent. (5.55)

   Statement (5.55) may be referred to as the System-Dependency of Uncertainty and Complementarity Principles (SDUCP).
9. Table 5.9 strongly indicates that the principles of uncertainty and complementarity are not confined to physics but are universal. Since complementarism (Sect. 2.3.4) is a philosophical framework based on the universality of complementarity and since the principle of complementarity is in turn thought to be related to that of uncertainty (see the second and third rows, Table 5.9), the question naturally arises as to how complementarism may be related not only to uncertainties but also to other cognate terms such as information (or *liformation* more generally, Sect. 2.3.1), energy (or *mattergy* more generally), and measurement (Plotnitsky 2006). One possible way to characterize the multifaceted relations among these terms is suggested in Fig. 5.11, utilizing the language of networks and the Peircean triadic template (see Fig. 4.6):

In Fig. 5.11, complementarism is suggested to be a network of three nodes – Gnergy, Mattergy, and Liformation – and three edges – Complementarity (1), Uncertainty (2), and Measurement (3). BPB stands for the Bernstein-Polanyi boundaries (explained in Sect. 3.1.5) that provides the context of discourses or specifies the system-dependency entailed by Statement (5.55). Just as "mattergy" embodies the intimate relation between *energy* and *matter* through Einstein's special relativity theory (Shadowitz 1968), so "liformation" embodies the inseparable relation postulated to exist between *life* and *information* in the gnergy theory of biology (Ji 1991, 2004b). Thus, as first suggested in (Ji 2004b), it may be concluded that:

> Just as matter is regarded as a highly condensed form of energy, so life can be viewed as a highly condensed form of information. (5.56)

Statement 5.56 may be referred to as the *information-life identity principle* (ILIP) just as $E = mc^2$ can be referred to as the *energy-matter identity principle* (EMIP).

5.3 Cybernetics

The term "cybernetics" comes from the Greek $\text{K}\upsilon\beta\varepsilon\rho\nu\acute{\eta}\tau\eta$ or kybernētēs, meaning "steersman," "governor," "pilot," or "rudder." Plato used the term to refer to government, but the term became widely used in modern times after Nobert Wiener published his book in 1948 entitled "Cybernetics, or control and communication in the animal and machine" (Wiener 1948). As the subtitle suggests, cybernetics is the science of control and *communication* in machines, both artificial and biological, that are endowed with the ability to achieve specific goals through feedback interactions. Both control and communication implicate information. Communication is concerned with encoding, transmitting, and decoding information, while control *utilizes* information. Hence, cybernetics can be considered to subsume information theory (see Sect. 4.3 for the concept of *information*).

5.3.1 Control Theory

Control theory is the science of controlling dynamical systems to achieve desired outcomes. It originated in engineering and mathematics but is now used in biology and social sciences. The concepts and principles developed in the control theory of artificial machines have been found useful in describing the behaviors of living systems and their components such as enzymes, metabolic pathways, and living cells themselves. Some of these concepts and terms are illustrated in Fig. 5.12. The desired output of a machine is referred to as *reference*. When one or more output variables of a machine must follow a certain reference, the *controller* of the machine manipulates the inputs to the system to obtain the desired output. A part of the output is directed to the *sensor* of the machine which feeds it back to the *controller* to adjust

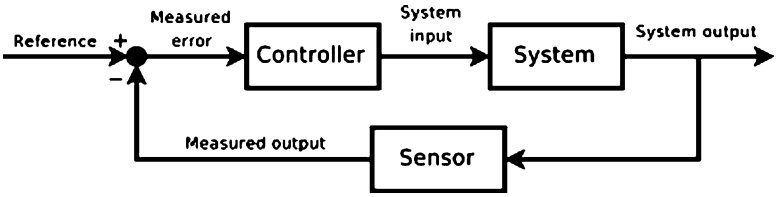

Fig. 5.12 A diagrammatic representation of a system with feedback control (Reproduced from http://en.wikipedia.org/wiki/File:Feedback_loop_with_descriptions.svg)

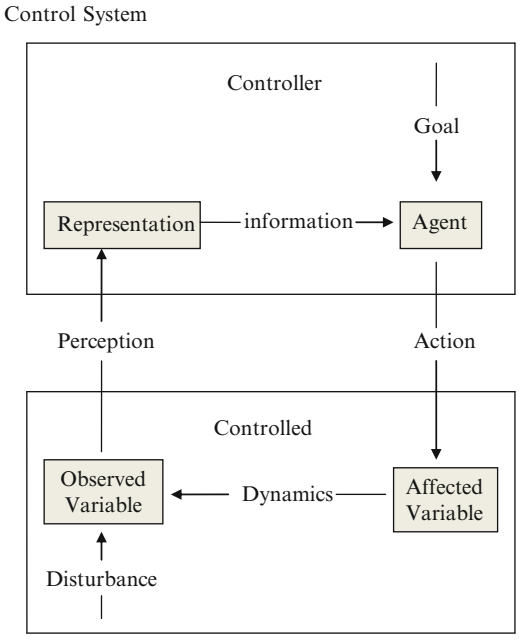

Fig. 5.13 The structure and function of a control system (Adapted from http://pespmc1.vub.ac.be/REQVAR.HTML)

the new input either negatively (leading to negative feedback) or positively (leading to *positive feedback*). In other words, feedback control is achieved when a portion of the output signal is operated on and fed back to the input in order to obtain a desired effect. A controller monitors its effect on the system and modifies its output accordingly. As an example, consider a thermostat. It has two inputs: the desired temperature or the reference and the current temperature (the latter is the feedback). The output of the thermostat changes in order to equalize the two inputs.

A more detailed diagram of the *control system* is given in Fig. 5.13. It consists of two subsystems – *the controller* or *controlling system* (denoted as C) and *the controlled* or *controlled system* (S). The interaction between C and S is asymmetric in that C has a complete control over S, to the extent of destroying the controlled.

Table 5.10 A comparison between thermodynamic and control systems

	Thermodynamic system (TS)	Control system (CS)
Scientific discipline	Thermodynamics	Cybernetics
Key characteristics[a]	(1) Energy, (2) Entropy, (3) T, (4) P, and (5) V	(1) Energy, (2) Entropy, (3) Controller, (4) Controlled, (5) Representation, (6) Agent, (7) Information, (8) Goal/Aim/ Teleonomy, (9) Action, (10) Perception, (11) Affected variable, (12) Observed variable, (13) Dynamics, and (14) Disturbances
Principles obeyed[b]	(1) First Law, and (2) Second Law	(1) First Law, (2) Second Law, (3) Principle of feedback control (Sect. 5.3.1), (4) Principle of the minimum energy requirement for information flow (Sect. 4.8), (5) Law of requisite variety (Sect. 5.3.2), and (6) Principle of Information and Energy Requirement for Organization (PIERO) (Sect. 3.1), which may be referred to as the *Law of Requisite Information* (LRI)
Relation[c]	TS > CS or TS < CS (depending on whether sets are defined extensionally or intensionally, respectively)	

[a] Some of the same concepts, factors and parameters essential for describing TS are also required to describe CS in addition to those unique to CS

[b] Thermodynamic laws are universal and hence obeyed by all material systems including CS. But there are the laws, rules or regularities found uniquely in control systems. These may be named as follows: (3) = the First Law of Cybernetics, (4) = the Second Law of Cybernetics, (5) = the Third Law of Cybernetics, and (6) = the Fourth Law of Cybernetics (see the second row and third column)

[c] All control systems are thermodynamic systems but not all thermodynamic systems are control systems

But S has only a small effect on C through the formation of perception. The controller consists of two components – *representation* of the controlled system and the *agent* responsible for the action of the controller. The relation between *representation* and *agent* is the *flow of information* which determines the actions of the agent. The controlled system can be described in terms of two variables – the *affected variable* that is altered by the action of the agent and the *observed variable* that is observed by the controller through perception. The observed variable also includes uncontrollable disturbances on the controlled system.

Just as *thermodynamics* is defined as the scientific study of the *thermodynamic system* (TS), *control theory* or *cybernetics* can be viewed as the scientific study of the *control system* (CS). In Table 5.10, TS and CS are compared in detail, treating them as sets of elements. The second and third rows of the table list two different classes of the elements of TS and CS. The second row lists system characteristics and the third row lists the laws and the principles being obeyed. Of the 5 elements of the TS set in the second row, only 2 are found in the CS set, while none of the 12 unique elements of the CS set is found in the TS set. All of the elements of TS in the third row are included as the elements of CS but none of the four unique elements of

CS are found in TS. Thus, at both these levels, more elements of TS are found to be the elements of CS than the other way around, which may be expressed as Inequality (5.57):

$$\text{TS} < \text{CS} \tag{5.57}$$

Inequality 5.57 may be interpreted as reflecting the relative complexities of TS and CS in the sense that

It takes a longer bit-string to describe a system viewed as a CS than as a TS. (5.58)

Based on the content of the third row of Table 5.10, it is clear that:

All control systems are thermodynamic systems; but not all thermodynamic systems are control systems. (5.59)

We may refer to Statement 5.59 as the "Principle of the Insufficiency of Thermodynamics for Controlled Processes" (PITCP). Statement 5.59 establishes that there are more thermodynamic systems than there are control systems or that CS is a subset of TS, leading to Inequality 5.60:

$$\text{TS} > \text{CS} \tag{5.60}$$

On the surface (i.e., on the syntactic or formal level), Inequalities 5.57 and 5.60 appear contradictory. However, on the semantic level, that is, if we take into account the different contexts under which the TS and CS sets are defined, no contradiction appears. There are two ways of defining a set – (1) *extensionally*, by listing sample members of a set, and (2) *intensionally*, by listing the characteristics of, or the rules obeyed by, the members of a set. It is here claimed that

If A is a subset of B, A is less complex than B extensionally and more complex than B intensionally. (5.61)

We may refer to Statement 5.61 as the "Complementarity of the Extensional and Intensional Definitions of a Set" (CEIDS), or, more briefly, the "Extension-Intension Complementarity" (EIC). Since the extensional definition of a set is akin to viewing a set *globally* and the intensional definition akin to viewing a set *locally*, EIC may be regarded as a species (or token) of what is often referred to as the "Forest-Tree Complementarity". Based on EIC, we can now account for the apparent contradiction between Inequalities 5.57 and 5.60 as a natural consequence of the complementarity between the extensional and intensional definitions of a set.

5.3.2 The Law of Requisite Variety

One of the most useful laws to be imported from engineering into biology is what is known in cybernetics as the Law of Requisite Variety (LRV). There are many ways

to state this law Heylighen and Joslyn (2001a, b) but the following definition adopted from Ashby (1964) is suitable for application to molecular and cell biology:

> When a machine (also called a system or a network) is influenced by its environment in a dominating manner (i.e., the environment can affect the machine but the machine cannot influence its environment to any significant degree), the only way for the machine to reduce the degree of the influence from its environment is to increase the variety of its internal states. (5.62)

The complexity of biological systems (or bionetworks), from enzymes to protein complexes to metabolic pathways and to genetic networks, is well known. One way to rationalize the complexity of bionetworks is to invoke the Law of Requisite Variety. We can express LRV quantitatively as shown in Eq. 5.63. If we designate the variety of the environment (e.g., the number of different environmental conditions or inputs to the system) as V_E and the variety of the internal states of the machine as V_M, then the variety of outputs of the machine, V_O, can be expressed as

$$V_O \geq V_E/V_M \tag{5.63}$$

One interpretation of Eq. 5.63 is that, as the environmental conditions become more and more complex (thus increasing V_E), the variety of the internal states of the machine, V_M, must increase proportionately to maintain the number of outputs, V_O, constant (i.e., keep the system homeostatic). Another way to interpret this equation is that, in order for a bionetwork to maintain its functional homeostasis (e.g., to keep the numerical value of V_O constant) under increasingly complexifying environments (i.e., increasing V_E), the bionetwork must increase its variety or complexity, namely, V_M.

The term "variety" appearing in LRV can be expressed in terms of either (1) the number of distinct elements, or (2) the binary logarithm of that number. When variety is measured in the binary logarithmic form, its unit is the bit. Taking the binary logarithm to the base 2 of both sides of Inequality 5.63 leads to Inequalities 5.64 and 5.65:

$$\log V_O \geq \log (V_E/V_M) \text{ or} \tag{5.64}$$

$$\log V_O \geq \log V_E - \log V_M \tag{5.65}$$

which is identical with the equation for LRV used by F. Heylighen and C. Joslyn (2001), except that the buffering capacity of the machine, K, is assumed to be zero here, that is, the machine under consideration is assumed to respond to all and every environmental perturbations. Since $\log V_x$ is defined as Shannon entropy H_x (see Eqs. 4.2 and 4.3), Inequality 5.65 can be transformed into a more convenient form:

$$H_O \geq H_E - H_M \tag{5.66}$$

where H_O is the Shannon entropy of the machine outputs, H_E is the Shannon entropy of the environmental inputs, and H_M is the Shannon entropy of the state of the machine or its controller. Two cautionary remarks are in order concerning Inequality 5.66:

1. The symbols for Shannon entropy, H, should not be confused with the symbol for enthalpy, H, in thermodynamics, and
2. The same term "entropy" is represented by H in information theory and by S in thermodynamics. In other words, there are two kinds of entropies – the *information-theoretic entropy* (referred to by some as "intropy") and *thermodynamic entropy*. There are two schools of thought about the relation between intropy, H, and entropy, S (Sect. 4.7). One school led by Jaynes (1957a, b) maintains that H and S are in principle identical up to a constant factor, whereas the other schools represented by Wicken (1987), myself (Ji 2004c), and others assert that H and S are distinct and cannot be quantitatively related (see Sect. 4.7).

Just as the Second Law of thermodynamics can be stated in many equivalent ways, so LRV can be expressed in more than one ways, including the following:

Simple machines cannot perform complex tasks. (5.67)

To accomplish a complex tasks, it is necessary to employ complex machines. (5.68)

Nature does not employ complex machines to accomplish simple tasks. (5.69)

If the internal structure of a biological machine is found to be complex, it is very likely that the task performed by the machine is complex. (5.70)

Thus, LRV provides one way to explain the possible biological role of the complex biological structures such as signal transduction pathways, transcriptosomes, nuclear pore complexes, both of which can implicate 50 or more proteins (Halle and Meisterernst 1996; Dellaire 2007). For example, it is possible that nuclear pore complexes had to increase the variety of their internal states to maintain functional homeostasis (e.g., transport right RNA-protein complexes in and out of the nuclear compartment at right times and at right speeds) in response to increasingly complexifying environmental (e.g., cytoplasmic) inputs or perturbations. In other words, nuclear pore complexes (viewed as molecular computers or molecular texts) had to become complex in their internal structures so as to process (or carry out computations on) more and more complex input signals from their microenvironment in order to produce the desired outputs without fail.

5.3.3 *Principles of After-Demand Supply (ADS) and Before-Demand Supply (BDS)*

There are three distinct ways for a system to interact with its environment or three distinct types of supply and demand: (1) The system adjust its internal states in

Table 5.11 Three mechanisms of interactions between systems and their environment predicted by the generalized Franck–Condon principle (Sect. 2.2.3). R_S rate of change of the system, R_E rate of change of environment, *BDS* before-demand supply, *SDS* synchronous demand and supply, *ADS* after-demand supply

Rates	$R_S << R_E$	$R_S = R_E$	$R_S >> R_E$
Mechanisms	BDS	SDS	ADS
Examples	Enzymic catalysis	Predator–prey interactions	Biological evolution

response to environmental demand (in which case the environmental demand must precede the internal state changes), (2) the system adjust its internal states simultaneously with the environmental demand, and (3) the system can readjust its internal state in anticipation of environmental demand (in which case the internal state changes must precede the environmental demand). We may refer to these mechanisms as (1) the "after-demand supply" (ADS), (2) the "synchronous demand and supply" (SDS), and (3) the "before-demand supply" (BDS), respectively. There are two rate processes involved – the rate, R_S, of internal state changes, and the rate, $R_{E,}$ of the change in environmental demand. There are three possible scenarios regarding the relative magnitudes of these rates as shown in Table 5.11, which also includes the suggested mechanisms for each scenario.

An example of SDS would be the uncertainty associated with a lion catching a deer because their running speeds are comparable, that is, $R_S = R_E$: Sometimes the lion succeeds in catching a deer and other times the deer gets away safely. An example of BDS is provided by the phenomenon of conformational rearrangements of enzymes (S) before they bind their substrates (E) since $R_S << R_E$, in agreement with the generalized Franck–Condon principle and in contradiction to the induced fit model of enzymic catalysis (Koshland 1958) (Sect. 2.2.3). Finally, an example of ADS would be the biological evolution where the life cycle of organisms (S) are faster than the rate of change of their environment (E), that is, $R_S >> R_{E,}$ so that, in order for organisms to evolve, the changes in their environment must first take place before better fit organisms survive and less fit ones get removed in order for the group (or lineage or taxon) to change its genome. Again this is the prediction consistent with the generalized Franck–Condon principle (Sect. 2.2.3).