Chapter 6
The Process of Deep Systems Analysis

Abstract The first component discussed in Chap. 5 is the deep analysis of a system of interest using a top-down decomposition procedure. This chapter will provide the guidelines for how this procedure integrates the objectives of a reductionist analysis with retaining the holistic aspects of systemness by using the recursive system definition of Chap. 4 that preserves the interrelations of subsystems at all levels of organization in the system. The procedure is one of "deep" analysis meaning that it is an algorithm for guiding a recursive process exposing increasingly deep details of subsystems and components until we come to stopping conditions, down any leg of the hierarchy based on finding "leaf nodes" representing "atomic" processes. We end the chapter looking at "advanced" concepts of complex systems such as fuzziness, adaptability, and evolvability considerations. These will be revisited in the coming chapters.

6.1 What We Seek to Achieve

In this chapter, we focus on the analysis phase briefly described in the last section of Chap. 5. This is the part of the process where knowledge of the system is obtained through deep analysis and captured in the knowledgebase. Guidance for the procedures comes from the formal definition of a system given in Chap. 4 along with the language of systems derived from the ontology of Chap. 3 and the formal definition. What we will be describing in this chapter is essentially the procedures to be followed in performing this analysis in the abstract, that is, as they apply to any arbitrary system. In the next chapter, we provide examples of how these procedures can be used to analyze three particularly complex specific systems. In Chap. 8, we will cover the nature of the knowledgebase itself—how it stores knowledge for retrieval and use, again as briefly described in Chap. 5.

G. E. Mobus, *Systems Science: Theory, Analysis, Modeling, and Design*,
https://doi.org/10.1007/978-3-030-93482-8_6

The procedures we describe are:

- Define the System of Interest (Level 0).
- Environment, Boundary, and Flow Analysis (Level -1).
- Recursive Decomposition of Subsystems (Level $1\ldots m$).

Within each of these procedures, we will cover the methods for collecting data and entering it into the data structures of the knowledgebase. It is the organization of the data in these structures along with the relations between these structures that turn the data into knowledge.

The work to be described in this chapter is not without predecessor thought. Specifically, the works of George Klir (2001) and Peter Checkland (1999) have been instrumental in forming the concepts presented here. Klir was a mathematician who was interested in the abstract representation of systems (as described in Chap. 4) and who developed a rigorous framework for thinking about systems, most particularly of what we now call the "hard" sort. His work, being primarily mathematical in nature, seems to have gotten lost in the general systems literature, at least in the Western world. Our aim is to bring his insights down to earth, so to speak, by making the procedures implied in his abstractions more operational.

Checkland investigated systems that involved human actors (agents) and complex decision-making and came to the conclusion that such systems could not be characterized in the same way the so-called hard systems were done. He (with others) developed the concept of soft systems to deal with much less well-characterized systems like organizations involving social interactions (which include human emotions and motivations, biases and beliefs). His work and thoughts are pursued today in the frame of organizational systems thinking. Without losing his insights as to what makes a soft system soft, we will attempt to show how more formal constructs can be brought to bear on such systems. Our objective is to show how all systems can be understood in the same framework of systemness and that doing so can give rise equally to scientific understanding of natural phenomena as well as being the basis for generating designs and policy prescriptions. In other words, to unify hard and soft systems under a single notion of systemness.

At the time that both of these thinkers were formulating their approaches there still existed formidable hurdles with respect to characterizing very complex systems, particularly human thinking. And so systems science has taken on a bifurcated set of tracks that cater to hard problems versus soft or wicked problems. Our work will attempt to demonstrate that the deficiencies in characterizing the hard aspects of so-called soft systems are giving way to more rigorous methods (e.g., functional imaging of living brains during perception and conceptualization). Thus, we claim, a general system understanding methodology applicable to both hard and soft systems is now amenable. We briefly examine the status of Klir's approach and that of Checkland's as they represent the dichotomy and then proceed to outline the methodology that we assert will reconcile it such that there is only one concept of systemness to be employed.

6.2 Perspectives on Systems Analysis

In the next two sections, we will briefly review Klir and Checkland to provide some framework for arguing the resolution between the hard and soft systems perspectives.

6.2.1 Klir's General Systems Problem Solver

The idea that a formal approach to understanding concrete and abstract systems through a systems-based methodology was described by George Klir (2001). His approach was very abstract and covered the range of systems problems[1] very generally. He established a basic knowledge (epistemological) framework as a hierarchy of system components and categories, then proceeded to sketch out how the problem solver (GSPS) would work to capture the system knowledge from a specific domain, concrete system.

The subject of this chapter is in line with Klir's concepts. What the chapter describes is the author's view of actual methods to be employed, starting with procedures for capturing what Klir referred to as system knowledge.

6.2.1.1 Epistemological Hierarchy

Klir starts with describing a way to categorize systems based on a hierarchy of forms. For Klir a system could be the actual entity of inquiry, the "thing" that is a kind of system or what he called a "source system" or also an "experimental frame." Or it could be a higher-level abstraction. The next level up from the source system was a "data system" in which actual measurements (and their number support) of parameters were to be stored. Figure 6.4, below (Sect. 6.5.1.5), shows how a data system is obtained by measuring a time series of output flows. Figure 6.5 goes on to show a source system fully instrumented and collecting both input and output flows over time. The combination of the source system and the data collected over an appropriate length of time constitute the data system.

In Sect. 6.5.3, below we see the next level in Klir's hierarchy. This is the construction of a generative system. From the analysis of the input/output data, we can estimate what is called a transfer function. Having such a function allows us to compute a semi-unique output from the system for any combination data on the

[1] Mathematicians tend to use the word "problem" to specify whenever we want to achieve something or figure out why something works the way it does, not just when something doesn't work properly and we need to figure out why. A biologist would describe the need to find out, for example, the details of a particular metabolic pathway as a challenge, but since nothing needs fixing would not consider this a problem. On the other hand, how life got started in the first place is still problematic since we don't have sufficient sources of information to construct a model.

inputs. In other words, we have arrived at a model of the system of interest that allows us to make predictions.

At the highest level in Klir's hierarchy is the "structure system." This is the composition of source/data/generative systems that produce higher order systems (what we have been referring to as the higher levels of organization). This is Klir's version of the recursive decomposition of complex systems into sets of simpler systems.

Using this hierarchy, systems can then be classified by combinations of these characteristics. **SE**, **SD**, **SG**, $\mathbf{S^2E}$, $\mathbf{S^2D}$, $\mathbf{S^2G}$ represent structures of source, data, and generative systems, including second order structures ($\mathbf{S^2}$), structures of structured systems.

6.2.1.2 Metasystems

Metasystems are categories of similar systems. So, for example, all living cells fit into the general category of "cell" even though there are significant differences between cell types (their underlying source, data, generative, and structure system characteristics may vary according to their "thinghood").

The **M** operator represents the categorization operator of systems of the same types as metasystems. Thus, **ME**, **MD**, and **MG** are constructions of the categories of all source systems, all categories of data systems, and all categories of generative systems, respectively. As with structure systems, higher order metasystems are permissible. Moreover, complex combinations, for example, a metasystem of structure system of source system is describable (Klir 2001, 87).

6.2.1.3 Conceptualization of Systems

Whereas Klir's description of system knowledge and a methodology for obtaining it was an abstract system for classifying kinds of systems and system components and for gaining system knowledge guided by this epistemological hierarchy, he did not provide a broad set of examples of how this was to be done. He also described the GSPS in very abstract terms, a computing system that contained systemhood[2] expertise (he imagined an automated expert system driving the internal operations). As with the epistemological framework he did not provide much detail on its operation and uses (see his block diagram, Klir 2001, 94). In this chapter, we begin to work out some important details of how a real system for system understanding, fulfilling the potential of the GSPS, might be realized and applied. Klir's examples tended to be mathematical or logical and relatively simple. While he did work with fuzzy system concepts (as described in Chap. 4), the kinds of system problems

[2] This is Klir's term which we take to be essentially what we have been calling systemness. He considers the world to be comprised of things that have specific thinghood qualities, for example, color or size, but also systemhood qualities, for example, the characteristics of being a system that transcend thingness.

called "wicked" (Checkland 1999), for example, social systems involving human decision-making, were not represented. The intent of the current work is to bridge the gap between "hard" systems knowledge and "soft" system methodologies and soft systems knowledge (Checkland 1999). The examples we will demonstrate in Chaps. 7 and 9 will demonstrate how the method of deep systems analysis can be applied to such soft systems and wicked problems.

Readers are encouraged to explore Klir's work, especially (2001) as it was extremely influential, or certainly inspirational in what follows.

6.2.2 Checkland's Soft Systems Methodology

One of the more influential voices in the systems thinking and its practice in the realm of "human activity systems" was that of Peter Checkland (mentioned above; see especially Checkland 1999) and his conceptualization of what he called "soft systems methodology"[3] (SSM). He recognized what he felt were some fundamental differences between engineered systems such as airplanes, space shuttles, and submarines, and social-based systems such as a corporation or non-profit charity. The former ones are characterized by "hard" requirements for behavior and engineers need only detail the specifications for performance, costs, and such, to have a basis for implementation. Human activity systems (HAS), on the other hand, have generally messy requirements for what the activity should be, even when the organization has well-articulated goals in mind. Associated with the non-hardness of HASs is the fact that human participants are the agents making decisions and taking action, and humans are notoriously not rational in the same way a mechanical system is rational (Kahneman 2011). Moreover, humans are subject to extensive noise and distortions in their perceptions as well as suffer from too much influence from ideological beliefs in their decision-making. In other words, it is generally the human factors that make decision processes in HASs messy and wicked.[4]

Soft-systems thinking, as Checkland characterizes it, derives from actual experiences of people trying to use general systems thinking to analyze wicked problem domains and finding that the engineering approach, hard-systems thinking, could not succeed in dealing with understanding such problems. On the face of it this seems like a reasonable conclusion and there are now two distinct schools of systems analysis in play, one for the so-called hard systems and the other for the soft ones. Figure 6.1 is adapted from Checkland (1999). It shows a process that is followed in SSM.

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[3] By "methodology" Checkland means a set of principles applied to a family of related methods developed to address a particular kind of problem domain.

[4] The term "wicked" is applied to problems that are too complex and are greatly underspecified so that finding solutions is highly problematic.

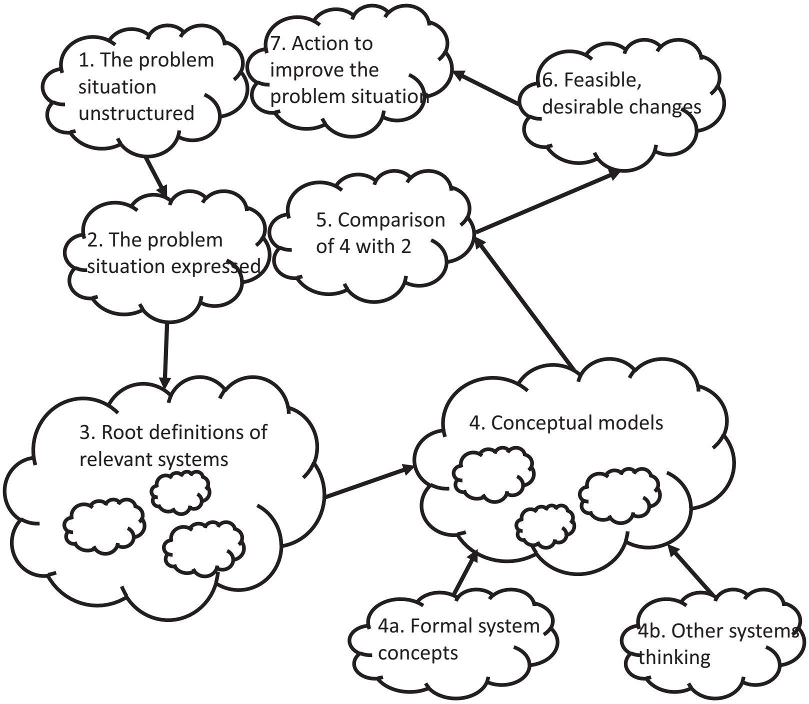

Fig. 6.1 Checkland's general outline of SSM, replicated from Checkland 1999, Fig. 6, Chap. 6, page 163

6.2.3 *Synthesis*

What is the actual difference between Klir's hard (and abstract) system and Checkland's soft (and concrete) systems? The framework definition presented in Chap. 4 provides a way to see that the differences might be best characterized not as a schism or dichotomy, but as a matter of degree of complexity and levels of organization. For Klir systems were abstract representations of "things"; he characterized the systemness as "thinghood." He sought to boil systems down to pure mathematics. Many other system scientists and engineers have come down on Klir's side but do not take the extreme constructivist position that Klir did. They view systems in the world as real and not just mental constructs. Still, they reserve the position that much of the systemness associated with these real systems is a matter of human consciousness. What we tried to do in Chaps. 3 and 4, culminating with Eq. 4.1 and subsequent equations, is shown that there is realness to systemhood that exists without the need for human observers. We argued, in fact, that the human brain itself is a computation system that is innately programmed to capture and encode systemness in the world. For Klir a system, $\boldsymbol{S}$, is just the tuple, $<\boldsymbol{T}, \boldsymbol{R}>$, where $\boldsymbol{T}$ is the set of things that comprises $\boldsymbol{S}$ and $\boldsymbol{R}$ is the set of relations between things. This is a very sparse definition and has been echoed by many other systems scientists.

Checkland could not reconcile the simple mathematical definition with what was for him the reality of human activity systems—messy "wicked" problems. With humans in the loop, he could not see how one could use the "hard" methods of engineering and mathematics to completely understand these systems. The vagaries of human behaviors made that impossible. The vast majority of system practitioners today still follow this line of thinking, not without cause. But is it a sufficient cause to warrant the seemingly binary schism between hard and soft systems? We do not think so.

Equation 4.1 and the recursive definition provided in Chap. 4 provide a structure that can capture (at least in principle) even the behaviors of human beings. For example, the *H* object, the history or memory capacity of a system (an example of which is Eq. 4.8), provides a very flexible mechanism for including detailed biographies, not unlike the data on user visits to websites analyzed by "big data" algorithms to learn something about that user and make predictions about where they might go next, or what ads they might like to see. The history can be used to track the pattern of a person's decisions and actions and thereby provide a model with a basis for predicting future behavior. Of course, this must be proven in the context of the system of system understanding being proposed in this book. But the existence of big data sets and their uses in modeling human behavior is already being done. There is no reason to believe it could not be expanded and refined in the context of soft system understanding.

Chapter 4 also provided an integration of several modes of communication and did not restrict itself to the mathematical definition alone. We proposed a language of system that can be expressed in, essentially, natural (verbal) language as well as graphical. We think this provides the resolution to treat these so-called soft systems in the same "formal" way one would treat the so-called hard ones. In Chap. 9 we will see this proposal in action, systems analyzing the human society economy (at least partially) which will definitely require that we take human beings into account.

With that we turn to the procedure for deep systems analysis.

6.3 Obtaining Knowledge of the General Systems

6.3.1 Formal Procedures

The point of this chapter is to develop and explain a set of formal procedures for analyzing any system, but particularly complex adaptive and evolvable systems. The complexity of these systems is so great that anything less than a formal method would easily get lost in the process. We know this is the case because it has been demonstrated time and again. Take, for example, the CAES we call "the economy" (see Chap. 13). Anyone who has given the workings of the economy any thought has conceived of it as a "system," but generally not in the way we propose. That is, they realize that there are many complex parts that interact with one another in complex ways but they rarely go much beyond this intuitive stance with respect to trying to better understand how the economy as a whole works. Formal methods as are found, for example, in the study of econometrics have been developed based on the typical modeling approach—best guess the variables and the equations that govern them. But as is becoming abundantly clear, this approach does not produce models that have any kind of valid predictive power. The problem with econometrics has been that the underlying assumptions of neoclassical economics (the academic version) are not based on any kind of reality! We will revisit this issue in Chap. 9 to show how a systems approach to economics produces a very different set of assumptions and, hence, different predictions about how the economy will behave in the future.

The procedures described in this chapter are formal in that they follow the principles of systems science and the definition of system given in Chap. 4.

6.3.2 Representations of the System

In this chapter, we will use several different representations of a system. The basic representation of a system is, of course, in the language of system, systemese as presented in Chap. 4. But there are different ways to structure the system descriptions that achieve different purposes. These are all interrelated and cover the same data, but provide different ways to perceive or use the data. The data itself constitutes the "knowledge" of the system and is the core representation. It is captured and stored in readily retrievable forms in the knowledgebase (see Chap. 8). This is a database system with the schema for relating data elements defined by the formal definition in Chap. 4.

A primary representation insofar as human perception and interpretation will be the various system "maps" or flow diagrams as we have been using. The map employs graphic icons that each represent parts of the system and show how those parts link together explicitly. See Fig. 6.11 below for a system map.

A third representation is the system "tree" diagram. This representation is, essentially, the system map viewed as if from the side with each sub-sub…system drawn at the appropriate depth in the tree. Figure 6.1, below, demonstrates this kind of representation.

The fourth form of representation is the set of equations that describe all of the subsystems' behaviors. All of the boundaries, flows, and interfaces, etc. are implicitly part of this representation even though not readily visible as such.

6.3.3 A Preview of the Most Complex Systems of Interest

In the Introduction, we introduced a type of system based on complexity and capacity to endure changes in the environment, the Complex, Adaptive, and Evolvable System (CAES). We further elucidated the nature of these systems in relation to the hierarchy of increasingly complex systems that have evolved through ontogenesis in Chap. 3. We have not, however, explicated the nature of a CAES sufficiently to make its existence relevant to the project at hand, namely the analysis of truly complex systems. In this section, we will provide a short preview of the nature of CAESs in order to rectify that shortcoming for now. This will be important because in Chap. 9 we will be delving directly into a CAES, namely the human social system's economy, using the methods described here, so a short preview of the nature of a CAES at this point will be necessary to make progress. For those who don't mind jumping around, we point out that Chap. 10 and Part 3 will provide a more complete exposition of the nature of the CAES model. What we offer here is just an appetizer!

The concepts of complexity and adaptivity in systems has been around for a fairly long time (Holland 1998, 2006; Kauffman 1993, 1995, 2000; Miller and Page 2007; Mitchell 2009; Nicolis and Prigogine 1989, just to name a few). All of these referenced authors also refer to systems that evolve to become better adapted to changed environments. But they rarely distinguish between the adaptivity of an individual entity versus the evolution of an entity to become more adaptive. In biological individuals the former capacity is fixed and the individual cannot itself evolve. Rather, the general category (species) to which individuals belong evolve through the reproduction of favored genotypes through generations. In suprabiological systems such as an organization (e.g., a corporation), however, the individual system has the ability to change itself (evolve) to become more fit. In general, the more complex systems are, the more adaptive they become, and ultra-complex systems, containing adaptive subsystems, may achieve a capacity called *evolvability*, or the ability to change themselves.

For now, put simply, a complex system is one that contains many heterogeneous parts and many levels of organization as covered in Chap. 4. At higher and higher levels of organization the complexity of subsystems includes the ability for those subsystems to obtain the capacity of adaptability or the ability to change internally in order to compensate for changes in the environment that have impact on the functions of the whole system (cf., Mobus and Kalton 2015, Chap. 10). For example, a system has the internal capacity to compensate for changes in the external temperature by increasing its internal temperature (warm-blooded animals). The underlying mechanisms are cybernetic subsystems that are involved in, for example, homeostasis and other response mechanisms.

6.3.3.1 An Adaptive System

Briefly, here, an adaptive system is one that is able to sense a change in a critical environmental parameter (e.g., temperature) and alter its internal operations in order to compensate for that change. The change, itself, must not be radical or outside of adaptable boundaries; the system is pre-designed to accommodate the range of changes but any changes outside that range will be detrimental and result in damage to the system. Homeostasis is an example of a mechanism that provides adaptivity. As long as the homeostatic range is within the preset (phenotypic) capacity of the system, the latter can adjust its internal operations to compensate. Adaptivity depends on a system having the capability to sense the change in the environment that is relevant to its functioning, make an appropriate decision to act to compensate for the change, and have the range of optional actions, what we call "requisite variety," and the necessary power in action to make the compensation effective. We will develop these ideas more fully in Part 3 of the book.

6.3.3.2 An Evolvable System

Adaptability can make a system resilient in the short run (assuming that the nature of the changes that warrant adaptive responses are within the ranges of adaptation built into the system). But in the case where changes are trending in a direction that will eventually lead outside the adaptive range that is built into the system, for example, the warming of the global atmosphere or the acidification of the oceans, then an additional mechanism for affording a greater capacity to modify the internal responses to those changes is needed. Evolvability is the ability to make or allow changes to internal mechanisms so that the system can accommodate changes beyond the typical range and it is a further method for achieving long-term adaptability to major changes. For example, in biological species, individuals may "suffer" mutations that do not immediately impact the phenotype under nominal (ordinary) within-range conditions, but under certain stressful conditions (i.e., a change in the environment pushing the limits of the range of preadaptive response) can be released so that some individuals exhibit an increased ability to adapt to the stressing changes. In a large population there will be a critical number of individuals with this particular capacity that they will be more fit than their conspecifics and survive the changed conditions thus leading to a new, more fit population. When enough such favorable mutations accumulate the individuals in this population may be so different from related (and historically ancestral populations) that they are effectively incapable (or unwilling) to mate, should they come back into contact.

The key to biological evolution, and evolvability within a species, is the fact that it is successful because of the size of a population that permits a large enough number of non-directing mutations such that at least a few of these will prove advantageous when the change comes about. When population sizes fall below a critical level, there would not be enough individuals with the "right" mutation to constitute a viable subpopulation. The population goes extinct.

Another proviso of this scheme is that the rate of changes must not exceed the rate at which potentially useful mutations can accumulate. For example, the current rate of global warming is extremely high in comparison to prehistoric events of this sort. So, it is very worrisome that many species, especially of higher multicellular organisms, may not be able to evolve at a sufficient rate to ensure viable individuals in any population, no matter how large.

Human beings are actually transitional as evolvable systems. They cannot modify their physiologies to be more adaptive, for example, being more heat tolerant. But they can modify their behaviors to achieve, effectively, the same end. This is because the human brain, with the remarkable capacities of the neocortex and, particularly, the prefrontal cortex, are able to act as an evolvable system, learning new concepts and altering behaviors to adjust to changing environments in ways that other animals cannot. Of course, not all human beings are adept at learning new knowledge and changing their concepts and behaviors (Mobus 2019). Only those with a sufficient capacity for "wisdom" are astute enough to observe the changes in their environments and intentionally alter their mental states leading to adaptive behaviors.

Human social systems, which includes societies, organizations, institutions, and government, to name a few, are the ultimate in evolvable systems in which intentional "mutations" lead to a long-term sustainable, viable system. In Part 4 of this book, we will revisit this aspect of social systems as evolvable based on the concept of intentional-organization and intentional evolution brought about by the nature of human consciousness and individual human evolvability.

6.3.3.3 CAES as an Archetype

A CAES is an archetype model, to be fully explicated in Chap. 10. An archetype model is one that specifies all of the generalized working parts of a whole system of the type. Used in analysis it guides the analyst by asserting what is to be expected to find as the analysis proceeds. It suggests questions that should be asked in the process of discovery. The patterns and sub-patterns presented in the archetype are found within the actual system being decomposed. Alternatively, used in design of a system, the archetype acts as a template for the design. Recursively applied as in analysis, that is, designing higher order systems with lower order CAESs, extremely complex systems with variations of adaptivity and evolvability can be composed, with appropriate interaction flows, to form the higher order CAES.

The actual origin of the CAES archetype model derived from an amalgamation, integration, and of the works of many previous systems thinkers. A partial list would include: Ashby (1958), Beer (1959, 1966, 1972), Boulding (1956), Checkland (1999), Churchman (1960, 1968a, b), Churchman et al. (1957), Forrester (1961), Fuller (1968, 1970, 1982), Klir (2001), Koestler (1967), Miller (1978), Morowitz (1968, 1992, 2002), Odum (1983, 1994, 2007), Prigogine and Stengers (1984), Rosen (1985, 1991), Shannon and Weaver (1949), Simon (1957, 1991, 1998), von Bertalanffy (1968), Wiener (1950, 1961). Along with the best ideas from these workers, the model incorporates more recent views of governance, agency, and agent theory, and the theory of nested economies (i.e., that the metabolism of cells is nested within the physiology of a multicellular being such as a human, and that physiology is nested within the extant social economy which supports life). Perhaps the biggest influence on the author's development of this archetype that is isomorphic across living and supra-living systems was the work of Stafford Beer (1959, 1966, 1972) who developed the Viable System Model (VSM) that includes many of the features found in the CAES model. More will be said of this in Chap. 10.

Since our main interest is in CAESs involving humans and decision processes (humans as agents) we will tend, in these pages, to focus on human social system subsystems. An extensive review of many different kinds of system with the properties of adaptivity and evolvability, including biological species, human beings as learners, human social systems, and ecological systems as subsystems of the Ecos have verified the main points of the CAES subsystem archetypes.

6.3.3.4 CAES Subsystem Archetypes

Chapter 10 will provide an overall description of the whole CAES model. But that model is composed of three sub-models that interrelate with one another, are tightly coupled. Every CAES will have these three sub-models. Chapters 11, 12 and 13 will proceed to treat each of these as a focus of discussion while pointing out how they cannot be handled as completely independent of one another. The sub-models are: agent and agency (how decisions are made and turned into praxis), economy (how work gets accomplished to provide the system with necessary goods and services for its own use but also for export), and governance (how decision types are distributed across the society and economy). The human social system is (or should be) a complete and viable CAES. But it is comprised of sub-social systems, organizations, institutions, and governments, which are themselves CAESs (or should be). In other words, larger CAESs have smaller CAESs within. Each smaller CAES has its own set of subsystems; its own agency, economy, and governance. Moreover, each of these subsystem CAESs may be found to be composed of yet smaller viable CAESs (or should be) such as departments, committees, and so forth. Finally, all of these sub-subsystem CAESs are composed of people (and increasingly AIs) who are obviously agents, but are also CAESs in their own right. Remember, the human brain is capable of evolving new thoughts and behaviors. Each human's economy is what we call its physiology. The brain is the main governance subsystem. The lowest level subsystems having humans as component parts may also have many CAS artifacts (e.g., computers) and many more simply complex or simple systems as tools for accomplishing the purpose of the CAES.

In the following chapter, we will explore how the methods described in this chapter apply to all kinds of systems, not just CAESs. But in Chap. 9 we will return to the analysis of human social system and go deep into the analysis of the social economy, in particular we will show how what most people think the economy is, is not at all what a viable CAES economy would be. A fuller explanation will need to await Chap. 13 where we reveal what a viable economy looks like from the standpoint of how a CAES works. But we think the reader will be able to see the main thrusts of the arguments given in Chap. 9.

6.4 "Deep" Analysis

As mentioned in the Introduction and discussed in the last chapter, the term "systems analysis" has been used in several different contexts since the mid-early twentieth century to the present. In engineering the design of a "hard" system (in Checkland's terminology, 1999, page A16), the term has been applied to the determination of what are called "requirements" and to an analysis of designs that would fulfill those requirements. What the "device" or system was supposed to do was a given and so the analysis phase was limited to how it should do it most efficiently and at least cost. In the field of information systems, where the term actually gave rise to a job title, "systems analyst," the work of analysis has never been to actually analyze the real system (a "soft" system in Checkland's terminology), that is the underlying organization to be served by the information SUBsystem.[5] In a vein similar to the engineering of physical artifacts, the purpose of the computational and communications subsystem was assumed a given. A "needs" analysis, in this field, amounted to little more than the same kind of requirements gathering as done in engineering.[6] The analysts asked the users/stakeholders what their needs were, assuming that the users actually knew what they needed (as distinct from what they wanted). This approach to analysis is at best partial and, depending on the experience and "wisdom" of the analyst, open to serious vacancies in the completeness of the resulting knowledgebase. Requirements are a pale image of the actual system.

What, then, is *real* analysis? The word "analysis" has several related definitions and is used in different disciplines in slightly different ways based on the medium of study in the discipline. The number one dictionary definition, however, encapsulates the broad meanings of the term in all of the various disciplines. This definition is from Dictionary.com: "1. the separating of any material or abstract entity into its constituent elements (opposed to synthesis)." The number 2 definition amplifies why separating something into its constituent parts is important. "2. this process as a method of *studying the nature of something* or of determining its essential features

[5] An information system is, in fact, just a subsystem of the larger supra-system which it serves. In Chap. 10, we elaborate the role of information systems, or actually the network of message flows and processing that is part of the governance subsystem of a CAES, like a corporation.

[6] The field of software engineering has always had difficulty being just like hardware engineering. Part of the problem stems from the nature of software, which is subject to a vast array of methods for achieving complex functions. Software development is more often like prototyping than product production. In Part 4 chapters we will return to this issue and suggest ways in which an overarching systems engineering process could be used to ensure better software development outcomes.