

Chapter 1 – Principles of Systems Science

Abstract Systems science, as a disciplinary basis for systems understanding and systems design has had very mixed reviews with regard to its efficacy of methods and successes in application. A central reason for this is that there is not now a single discipline of systems science that is taught as a core topic and there is not a unified concept of systems science being practiced in the field. There is, however, a strong intuitive notion of systemness and many systems aspects and methods being applied to problem solving. There is a strong notion that most of the major problems facing humanity are “systemic.” *The Principles of Systems Science* (Mobus & Kalton, 2015) was the first major attempt to reconcile and reunify the disparate aspects of systemness, showing how various aspects relate to one another. In this chapter we attempt to show how the principles outlined in that work may be applied to develop a single, consistent concept of a systems approach that is transdisciplinary and comprehensive. This leads to a set of methodologies (explicated in Parts 2 through 4) that will demonstrate how systems science can become a disciplined and principled way to tackle complex and important problems.

1.1 The Systems Approach

Within the sciences, engineering, management, and governance disciplines¹ a relatively new approach to investigation and design has developed over the last several decades². It is generally called the “the systems approach” to the discipline. What exactly do we mean by the “systems approach” and how does it differ from what we ordinarily think of as science and engineering practices? This book will attempt to answer that question and, in addition, demonstrate how a strong systems approach can be actually implemented. We will explore what difference it can make to various disciplines, and why it is crucially important to pursue in order to gain deep understanding of our world, especially our social systems and cultures.

The concept of a system (section 1.2 below) is a fairly easy one to grasp because our world – and the perceptions we have of that world – is organized into objects and interrelations between those objects, including ourselves as objects being in the world. Our brains evolved to grasp systemness because that is how the world is and grasping it makes us more fit evolutionarily. As a result, we intuitively understand the world (Chapter 3 will delve into this aspect). Systemness

¹ Through the rest of this book we will use the term *scientist* in the very broad sense to mean someone who discovers new knowledge, be they facts, principles, or ways of doing things. We will use the term *engineer* to mean someone who designs new objects, processes, or social policies. Thus someone who discovers a new market possibility in business would come under the term scientist, even though they are not necessarily using a strict scientific method. Someone who designs a new department to produce the new product is an engineer in this general sense.

² It is actually a bit difficult to put a definitive time frame on this development as it has entered the discourse of different sciences and engineering at different times. When the concept of a general systems theory was first emerging in the post-WWII period, several of the sciences, including management science, adopted aspects of systems science, as it was understood originally, quite readily, but possibly prematurely. Systems science has matured since then and the current discussions of the systems approach to understanding phenomena have re-emerged in multiple arenas in concert with the concepts of multi-disciplinary research.

1 is a recognizable property of objects and their relations and it does not matter at what scale of
2 space or time that we are observing. It does not matter what *level of organization* we look at, we
3 see systemness automatically. Elemental atoms are systems, as are living entities, as are
4 societies. Thus, the application of systems science as an approach to practicing the other sciences
5 promises to bring a new level of rigor to those studies beyond an intuitive recognition of
6 systemness.

7 As Peter Checkland observed, “What distinguishes systems [as a subject of the study of
8 systemness] is that it is a subject which can talk *about* the other subjects. It is not a discipline to
9 be put in the same set as the others, it is a meta-discipline whose subject matter can be applied
10 within virtually any other discipline”, [emphasis in the original] (Checkland, 1999, page 5). In
11 other words, systems science is a meta-science, the findings of which may be applied readily in
12 the other sciences. This is what we mean by a “strong” systems approach.

13 Currently, the need for a systems approach is intuitively understood by many scientists and
14 engineers because they are undertaking work that involves high levels of complexity in terms of
15 the numbers of interacting component parts and the heterogeneity of those parts. In the sciences,
16 the subjects of study involve phenomena that are traditionally studied within a specific discipline
17 like genetics or biochemistry but now combine in more complex levels where the knowledge and
18 skills of several traditional disciplines are needed. They recognize that the traditional disciplinary
19 phenomena cannot provide explanations for the complex ones that now take center stage. These
20 cannot be understood through just one discipline alone; they require transdisciplinary
21 approaches. Similarly, the kinds of engineering projects that are being tackled today cannot be
22 handled by one engineering discipline alone. Nuclear power plants, space shuttles, and even
23 commercial aircraft are not simple systems any longer. They are systems of systems – complex
24 objects that require the coordinated efforts of many engineering disciplines to design, produce,
25 deliver, and monitor for performance and improvement. Similarly, large multi-national
26 corporations and non-governmental organizations (NGO) have become extremely complex in
27 their operations requiring well thought through organizational, policy, and procedural designs.

28 Unfortunately, intuitions about systemness are not nearly enough. While many scientists and
29 engineers have been pioneering the use of systems thinking in pursuing their research and
30 designs, the efforts have been largely ad hoc, not necessarily integrated, and not generally based
31 on any central principles of systems science that could provide guidance to their efforts. Several
32 examples from both the sciences and engineering provide a sense of this early, formative, but
33 still immature notion of the systems approach.

34 To further clarify the issues involved we will describe what is meant by system, system
35 theory, system science and other relevant concepts. Figure 1.1 shows these and their relations to
36 one another.

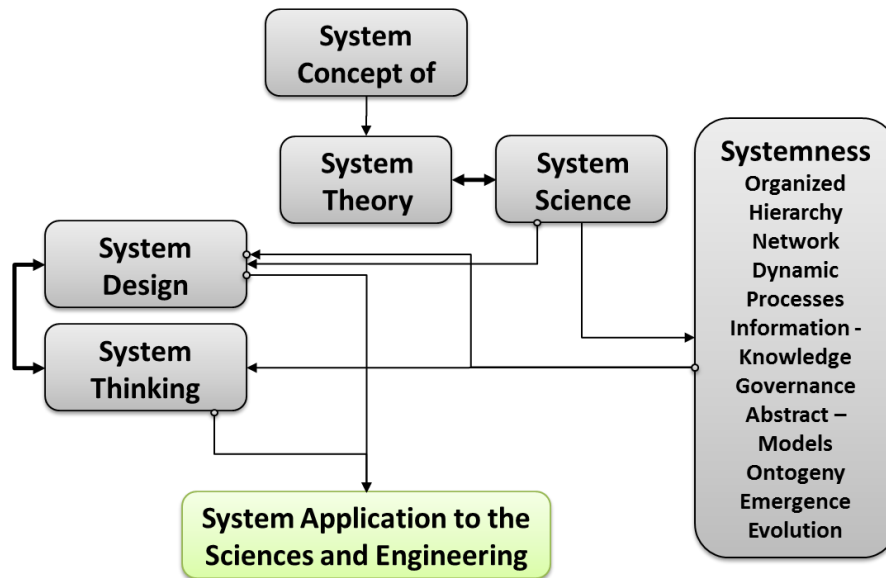


Fig. 1.1. The various areas of thought related to systems (grey) and how they influence the other sciences and engineering practice.

We start with the basic concept of a system as a thing, a whole entity and consider what that means. For this we propose a theory of system as an object of study and develop a science of system to determine what attributes and characteristics systems have in general (i.e. make for a general system theory, von Bertalanffy, 1968). System science leads us to discover these attributes, which, in turn, we posit must be found for anything we would call a system. The attributes, etc. taken together in concert we assert are principles of systemness, the properties of being a system (large grey box), elaborated in section 1.3 below. Both system science and the principles contribute to our ability to design artifacts, from machines to organizational and social policies. They also contribute to providing deeper thinking about the various systems we find in the world naturally. System design and system thinking together guide actions in analysis and understanding of artifacts and natural systems in the world (concrete systems). And so these contribute to the application of system concepts to the other sciences and engineering (green box).

This is our road map for applying system principles to understanding the world, including the things we invent.

1.1.1 Systems Intuitions, Thinking, and Sensibility

In the next two chapters we will be developing a “universal” language to be used in describing both qualitative and quantitative aspects of systems. The argument for the universality of this language is based on concepts developed in psychological linguistics having to do with

1 how the human mind uses an internal language of thought (LoT)³ to construct and think
2 thoughts. Unlike public, natural languages which are acquired through learning, LoT is natural to
3 the brain and is fundamentally the same in every human being. Like public languages, it has an
4 internal syntax and symbolic representations of concepts. This subject will be further explained
5 in Chapter 3. Public, natural languages are thought to translate into LoT representations and
6 syntax for internal, subconscious processing. That is, what we say in our languages is the result
7 of thinking in LoT translated to words and sentences in our learned public languages.

8 In this chapter we introduce LoT to make an argument about the nature of systems thinking.
9 That argument is that LoT, sometimes referred to as “mentalese,” is actually the language of
10 systems, or “systemese.” We perceive systemness in the world because our brains are hardwired
11 to do so. And our brains are so hardwired because the patterns of aspects of systemness are
12 objectively in the world. Humans, indeed all living things, evolved to have this perceptual
13 capacity at whatever level of organization (that is their econiche) they are embedded⁴. They
14 succeed in interacting with the other relevant systems in their worlds by virtue of their own
15 information processing capacity being based on systemness itself. Systemness can be thought of
16 as the fundamental organizing framework for the Universe. Therefore, systemese is a basic
17 template for describing the structures and functions of objects in the world. And because this is a
18 built-in language, in the brain, its causal effectiveness is largely subconscious. Until, of course,
19 the systemese sentences get translated into a public language – the one we hear inside our minds
20 when we are consciously thinking.

21 When notions of systemness are brought into conscious awareness, that is when they are
22 made explicit, we human beings are very quick to grasp how they apply. We can, without much
23 effort, see that many kinds of objects in the world are connected with other objects, that they
24 often have causal influences that follow time’s arrow. We can perceive readily that certain kinds
25 of objects have internal processes and internal components that interact with one another to
26 process inputs into outputs. This is how things work in the world so it is not at all surprising to
27 find that our brains evolved to capture these aspects of the world. Our brains, in fact, build
28 models of those things in the world that we observe – we call them concepts. And we use those
29 models to make “predictions” about what will happen in the future.

30 All human beings, thus, have deep intuitions about systemness and how the world is
31 composed of systems interacting with other systems, being part of larger systems. What we think
32 happens in humans is that this internal LoT is linked with a specialist subsystem in the brain that
33 encodes special “vocal” symbols and links these with the internal symbols of systemness. For
34 example, every human being has an intuition about the nature of a stock or reservoir as a

³ A more complete discussion of LoT will be presented in Chapter 3. Interested readers may want to take a look at this Wikipedia article in preparation for that discussion:

https://en.wikipedia.org/wiki/Language_of_thought_hypothesis Accessed: 10/21/2016.

⁴ We ordinarily think of animals with brains as having perceptions of the world. But, plants, and even bacteria, receive messages from their environments and behave in response.

1 container that receives input flows, stores whatever that flow consists of temporarily, and has
2 output flows that lower the level of the stock. That basic concept can be translated into a gas tank
3 in a car, or a bathtub, or a lake, or a parts inventory, or any other specific container that acts to
4 temporarily store a substance. According to LoT theory the brain has a “primitive” representation
5 of a stock element that can then be particularized for different real world representatives. This
6 mapping of physical instances in the world to a general concept in the mind is thought to be the
7 basis for metaphor and analogy. More details on the mechanism and its workings will be found
8 in Chapter 3.

9 **1.1.2 Examples of the Systems Approach within Disciplines**

10 **1.1.2.1 Systems Ecology**

11 Pioneers in the science of ecology such as the Odum brothers, Howard and Eugene⁵, deeply
12 understood the need to study ecological environments as systems. The term ‘ecosystem’ denotes
13 the idea that there are structures, part of the Earth’s subsystems, which have identifiable and
14 isolatable characteristics that determine or contribute to the biota that reside in those subsystems.
15 Howard Odum developed a language of systems based on the flow of materials and energies
16 through an ecosystem that could be mapped and modelled and that went far to explain how those
17 systems behaved as a whole.

18 Energy flows have been formalized in the model of food webs⁶ but even more complex
19 relations between species of plants, animals, fungi, and bacteria are now routinely studied in this
20 field. The concepts of energy flow and network relations are keys to the study of systems
21 ecology (principles 4 & 3 below). However so is the idea that ecosystems evolve over time. The
22 concept of succession is also an important aspect of the systems nature of ecology (see principle
23 6 below).

24 It is safe to say that systems ecology is one of the more advanced examples of the systems
25 approach used in a science. The application of many other principles, as discussed below, to
26 systems ecology is, however, somewhat spotty and not particularly integrated. For example, little
27 work has been done on exploring the nature of information and knowledge encoding (principle
28 7) as integrated with those described above. The field of ecological remediation touches on
29 principles 11 and 12 below, but only incidentally, intuitively.

30 Systems ecology is at the forefront of application of systems thinking to the science⁷. Other
31 sciences are starting to follow suit. For example, psychology, sociology, and neurology are
32 making forays into the systems approach as they expose the complexities inherent in their

⁵ See Wikipedia: Howard Odum, https://en.wikipedia.org/wiki/Howard_T._Odum and Eugene Odum, https://en.wikipedia.org/wiki/Eugene_Odum.

⁶ For a fairly comprehensive review of this topic see the Wikipedia article: https://en.wikipedia.org/wiki/Food_web accessed 10/19/2016.

⁷ See the Wikipedia article: https://en.wikipedia.org/wiki/Systems_ecology Accessed 11/2/2017.

1 subjects. Even so, they are tackling these issues in less than principled manner that will be
2 suggested in this text.

3 **1.1.2.2 System Dynamics**

4 One of the most successful uses of the systems approach to understanding complex systems
5 has been the development of the system dynamics (SD) modeling method. Developed by Jay
6 Forrester at MIT, SD has provided a wonderful tool for analyzing and simulating complex
7 systems (those having feedback loops internally). SD can be applied to an extremely wide
8 variety of systems, ecological (Ford, 2010), industrial (Forrester, 1961), and global (Meadows, et
9 al. 1972; Meadows, et al. 2004). SD modeling allows a scientist or engineer to reduce a system
10 of interest to an abstract set of stocks, flows, and controls that represent the dynamical aspects of
11 a system. Implicitly, these models also represent the networked nature of influences (flows of
12 information) that lead to the overt behavior of the systems modeled.

13 **1.1.2.3 Systems Management**

14 How to organize and manage an enterprise is the subject of systems management. The
15 enterprise is the system and the methods of analysis and design based on systems principles are
16 applied in order to achieve an optimal design. Many ideas applied to management, especially
17 operations and logistics management, derived from the field of operations research⁸. Major early
18 proponents of this field, and its implementation in management science, were Stafford Beer
19 (1959, 1966, 1972), C. West Churchman (1960, 1968a, 1968b), and Churchman along with
20 Russel L. Ackoff and E. L. Arnoff (Churchman, et. al, 1957).

21 Another champion of systems thinking applied to human organizations was, as already
22 mentioned, Peter Checkland (1999). An organization is an incredibly rich object for system
23 study. It is, or can be, completely transparent to the analyst's probes. Subsystems and sub-
24 subsystems are generally readily identifiable (e.g. departments). The behaviors of the various
25 subsystems are mandated by their production functions, which are generally well known (e.g.
26 accounting is standardized). And the main concern, from a systems perspective, is to carefully
27 design and regulate the information systems that provide inter-departmental and division
28 communications for the purpose of the cybernetic management functions (i.e. management
29 decision making). So important is this latter aspect that today the term 'information system' is
30 often taken as synonymous with the term 'system' by itself. Whenever someone refers to 'the
31 system' they are likely referring to the information⁹ and knowledge infrastructure.

32 Recognizing that organizations are organic, evolving and adaptive systems, Peter Senge
33 (1990) developed the theory for how an organization's information and knowledge infrastructure

⁸ See the Wikipedia article: https://en.wikipedia.org/wiki/Operations_research. Accessed 11/2/2017.

⁹ See the Wikipedia article: https://en.wikipedia.org/wiki/Management_information_system. Accessed
11/2/2017.

is the basis for successful adaptation in changing environments. He embedded this concept within a systems thinking approach (the fifth discipline) to understanding organizations.

1.1.2.4 Systems Engineering

Any activity that involves designing a complex artifact is in the domain of an engineering practice. To a large extent the design of an enterprise, as described above, can be an engineering exercise. Chapter 13 will provide a general overview of the systems engineering process as it will incorporate the methodologies described in the following chapters.

Design is a creative process in which a system that has not previously existed, or existed in a desired form, is specified for construction. Engineering is the process by which design options are tested and improved based on principles (and laws of nature) so that the finally constructed system is capable of delivering its intended purpose, usually at a sustainable cost (in energy and material inputs) and over an extended time (its intended life cycle).

In today's world the nature of so many services (e.g. infrastructure like power and other utilities) and high-tech products (e.g. the Internet of Things¹⁰). A new class of artifacts that combine physical work with artificial intelligence (i.e. robots like self-driving vehicles) called cyber-physical systems¹¹ can only be approached as complex systems requiring a systems approach to analysis and design.

It is no longer possible to just put a few mechanical or electrical engineers on the job to create these artifacts. In addition to the specialization of the traditional engineering approaches, a meta-engineering discipline is needed to coordinate and integrate the efforts of the disciplinary engineers. This is the role of systems engineering¹².

1.1.3 Possible Issues with Current Practices

As pointed out above using the systems approach, or systems thinking, in these and many other fields has been based on more intuitive and ad hoc methods. Systems intuitions turn out to be strong in the sense that the human brain is actually designed to perceive systemness (the next two chapters will develop this notion as the basis for developing a “universal” language of systems that can be used by any human being to communicate ideas about systems). Hence, such intuitions are reasonably good, at least in the way they frame thinking about complex things. But this is only a start to using systems principles rigorously in order to obtain deep understanding of the systems of interest in any domain.

The biggest issue with current practices is that often time practitioners adopt a fairly limited framework for approaching their subjects. For example, it is often the case that researchers using

¹⁰ See the Wikipedia article: https://en.wikipedia.org/wiki/Internet_of_things. Accessed 11/2/2017.

¹¹ See the Wikipedia article: https://en.wikipedia.org/wiki/Cyber-physical_system. Accessed 11/2/2017.

¹² See the Wikipedia article: https://en.wikipedia.org/wiki/Systems_engineering. Accessed 11/2/2017.

1 systems thinking get stuck in one of the many facets of systems science and attempt to explore
2 and explain phenomena from that facet alone. They may pursue modeling with system dynamics,
3 or use network theory or information theory as their main focus of study. Of course, these facets
4 need focal study at some point in developing a systems approach to the topics. However, they
5 cannot be the sole set of conceptual and methodological tools used to gain deep understanding.
6 **All of the principles of systems science have to be taken together in order to fully grasp the**
7 **nature of phenomena.** Developing a theory based on only one facet, or principle, is inadequate
8 for complete and deep understanding.

9 For example, dynamical behavior is, of course, an extremely important aspect of a system.
10 And the ability to model the components that lead to the overt behavior is crucial to
11 understanding the internal aspects of the system.

12 But dynamics, although extremely important, is just one aspect of a system that needs to be
13 taken into consideration when attempting to understand the whole system. For example, SD does
14 not directly deal with boundaries or boundary conditions. Boundaries are assumed by the
15 modeler, as are sources and sinks. Flows coming in from sources are specified, as are flows
16 going out to sinks. But in neither case is there an explicit model of the interface between the
17 system of interest and the external environment. In real systems this is a function performed as
18 part of the boundary. In most cases the model builder is required to define the boundary
19 artificially (or arbitrarily). This can have some advantages, for example when the modeler is only
20 interested in some very particular aspects of the whole system and needs to produce a very
21 abstract version. But as often as not, the modeler ends up ignoring or not being cognizant of a
22 mechanism that can have a disproportionate effect on what they are interested in under certain
23 conditions. For example, say a model has been constructed of a lake ecosystem not taking into
24 account the eutrophication of the lake due to nutrient runoff upstream in the watershed (from
25 agricultural sources like cattle manure ponds). That model cannot predict the die-off of fish in
26 the lake due to depletion of oxygen from the eutrophication event. The modelled system may
27 often display the expected dynamics that mimic the real physical system except when the real
28 system is subjected to those unexpected conditions.

29 Granted that researchers and engineers tend to specialize in their preferred sets of concepts
30 and methodologies to obtain a degree of expertise (and guarantee quality of their efforts) and that
31 this is not necessarily a “bad” thing. Nevertheless, a complete systems approach has to link
32 understanding of one principle facet to all of the others in order for scientists and engineers to
33 claim holistic understanding.

34 One route to this end may be to form inter- or transdisciplinary teams to ensure
35 completeness of coverage. Even if this is done, however, the members of such teams will need to
36 share a common understanding of what a system is and a language with which to communicate
37 with one another.

Another approach, the one which this book will explicate, is that the mere fact of having such a common (meaning universal) system language will help researchers and engineers, regardless of their specializations, to see the whole system because it provides a principled framework for delving into the systems of interest. Ideally, not only would the language assist the specialist identify those areas they need to cover external to their specialization, but the language should help non-specialists or non-technical people (the proverbial users or stakeholders) grasp the nature of the systems being considered.

1.1.4 A Principled Systems Approach

The examples above demonstrate that scientists, managers, and engineers well understand the need to apply concepts of systemness to their subjects in order to grasp a more holistic understanding of the phenomena or what they are trying to achieve. Clearly the need for a systems theory that underlies and supports these approaches is demonstrated. What has been lacking is an actual set of principles that are integrated across the systems science spectrum of subjects that would provide a basis for pursuing a “true” systems approach. That is, an approach that examines every aspect of systemness in the system of interest, leaving no aspect uncovered so that a holistic understanding results.

In the section below, 1.5 – What Goes Wrong, we examine what can happen (and does all too often) when a “weak” systems approach is applied to the understanding and design of a system. Ironically, this system is in the category of systems from which the word itself became a household term, the world of information systems (computers and communications) deployed to improve the management of organizations. The field, today, is generally referred to as Information Technology (IT) since the use of computing and communications technologies cover much more than just management information systems. As we will demonstrate below, the analysis of IT systems is not as principled as practitioners have assumed it to be. It is, rather, a collection of believed best practices. In particular the area of systems analysis is extremely weak and as a result, too many designed and developed systems experience one or more project failures that materially affect the effectiveness and/or cost of the system. While many problems arise due to the nature of computer programming (and the inherency of errors in producing code) these are technically fixable. The other kinds of errors are found in the designs

In this book, we will first review, briefly, the principles of systems science as described in Mobus & Kalton (2015), *Principles of Systems Science*, which is a comprehensive coverage of all currently understood aspects of system science. We will introduce all of those aspects and then throughout this book, demonstrate how they are used to obtain a holistic understanding, a deep understanding, of the systems studied by the sciences and those to be designed by engineering. The rest of Part 1 will first establish the theoretical underpinnings but the rest of the book is devoted to methodologies and examples of their application to real-world systems of great interest.

1.2 The Concept of a System

The concept of something being a system, or possessing the aspects of systemness, is, in one sense, simply a construct of the human mind, using systemese to describe the organized but complex phenomena it encounters. The brain treats things as systems because that is how it thinks. On the other hand, the model (concept) it is constructing is based on a reality in the physical world. We make a distinction between systems that are concrete, real things, and systems that seem ephemeral, conceptual, abstract, models that have their own kind of reality. As we discuss below, however, even the latter kind of system is a real thing. A concept in the mind, or a simulation model running on a computer consists of real physical structures and processes that, through a process of abstract representation, are constructed so as to have isomorphic relations with the real things out in the world¹³.

1.2.1 Definition

In chapter 3 we will provide a formal definition of system from which we derive a language of systems. This language is instrumental in pursuing understanding of systems through systems analysis and modeling. For now, let us look at an informal, qualitative, definition that will be sufficient to motivate the subjects covered till we get to chapter 3. It is important to note that there are many ‘informal’ definitions of systems that have been advanced over the years since the concept of things or processes as systems was formed in the early 20th century. While some of these definitions sought parsimony, looking for the simplest definition, others sought completeness. Most, however, agreed on the main attributes of something being a system.

For our purposes a concrete, ‘real,’ physical system is any identifiable object or entity that is composed of an internally organized set of heterogeneous components, each of which can be a subsystem, or, in other words, a system in its own right (recursive definition). Below we describe some other kinds of systems that on first pass don’t seem to qualify as physical or concrete systems, e.g. abstract or ‘conceptual’ systems. However, we shall argue that on closer examination even these meet the definition as given here.

A system is bounded in some manner such as to maintain unity-hood and be distinguished from the rest of its environment¹⁴. Substances such as materials, energies, and messages can,

¹³ There is a long-standing debate among some systems theorists, those who hold that systems conceptualization is strictly a mental construct (constructivists) and those who hold that real things in the physical world are systems (realists). This debate, however, is very much like the old nature-vs-nurture debate that raged before the link between genetics and development (ontogeny) became clear. Both nature and nurture are at work in eliciting form and function in living things. Similarly, we hold that both constructivism and realism are describing one single reality but from two different perspectives.

¹⁴ A distinction between a real system and a model of a system needs to be made. Real, concrete systems have real, though sometimes fuzzy boundaries. Models of systems are mental constructs in which a considerable amount of abstraction has resulted in leaving some things out. The boundary of such a model system is often more a construction of the modeler’s choices rather than a real boundary. This topic will be developed further in the chapters ahead.

1 cross the boundary, either entering or leaving the system, and usually in a regulated fashion.
2 Generally, not just anything can get inside or leave, only particular materials or energies are
3 permitted. However, systems might be subject to unregulated disturbances of various sorts.

4 In general, systems process inputs to produce outputs (material, energy, messages, or
5 forces). Inputs are received from sources in the environment and outputs go to sinks (both of
6 which may be minimally modeled). Figure 1.2 shows a generic model of a ‘physical’ system.
7 Technically, Figure 1.2 is itself an *abstract* system since it assigns names to the parts, e.g.
8 “boundary” is the name of the barrier that segregates the insides from the outsides of a real
9 system. It stands for a concept, the act of “protecting” the internals of the system from external
10 disruptions. Figure 1.2 depicts what we will call a “crisp” system. That is it represents a system
11 that has an identifiable boundary, environmental entities, and which can be deconstructed in a
12 straightforward way. Most systems in the world are not crisp. They are what we will call
13 “fuzzy.” That means it may be difficult (with whatever analytic tools are available) to define the
14 boundary, the flows or environmental entities, and the internal organization may be highly
15 indefinite. Figure 1.3 provides an alternate representation of fuzzy systems (and environments)
16 that implies the difficulty of finding hard definitions. Fuzziness (which will include messy
17 complexities, uncertainties, and ambiguities) is a major challenge in understanding systems, but,
18 as will be argued in Chapter 5, this has always been the challenge in the sciences using
19 reductionist methodologies to drill down to lower levels of organization (i.e. finding out how a
20 system works and how it responds to its environment). In Chapter 5 we will show how we
21 approach the analysis of a fuzzy system in terms of approaching the status of being a crisp
22 system. In Chapter 3 we will provide the fuzzy set framework of making this possible.

23 Checkland (1999) has made a distinction between ‘hard’ and ‘soft’ systems, along these
24 same lines. He notes that “human activity systems,” that is everything humans do in
25 organizations and governance, are not definable as a concrete system (e.g. Figure 1.2) due to the
26 extraordinary number of additional factors such as value systems affecting decision processes.
27 For the latter case he developed a ‘soft systems methodology’ (SSM) that recognizes these
28 complexities and eschews any attempt to treat human-based systems as if they were artefactual
29 or simpler biological (natural) systems, yet still recognizing the systemness of such organized
30 activities. It remains an open question, currently, as to whether the fuzzy system openness to be
31 described in Chapter 3 will provide an effective middle ground between SSM and hard systems
32 with respect to analysis and, for example, the design of public policy. In Chapter 6, and later in
33 Part 4, we will show how the fuzzy aspects of the definition developed in Chapter 3 may be used,
34 nevertheless, to analyze and understand social systems, or subsystems thereof. Rather than treat
35 systems as black and white (hard vs. soft), our approach attempts to ameliorate the two extreme
36 versions so that a consilience might provide greater insights at both ends of what we think is a
37 spectrum. There is, we contend, no excluded middle here. Some systems will prove to have both
38 hard and soft attributes and in order to be truly integrative we have to find a way to work with
39 both simultaneously. After all, the human social system (HSS) is a subsystem of the natural

- 1 Earth supra-system. Our whole existence depends upon our ability to understand the interactions
 2 between the hard systems of nature, the hard systems of technology, and the soft systems of
 3 human activities.

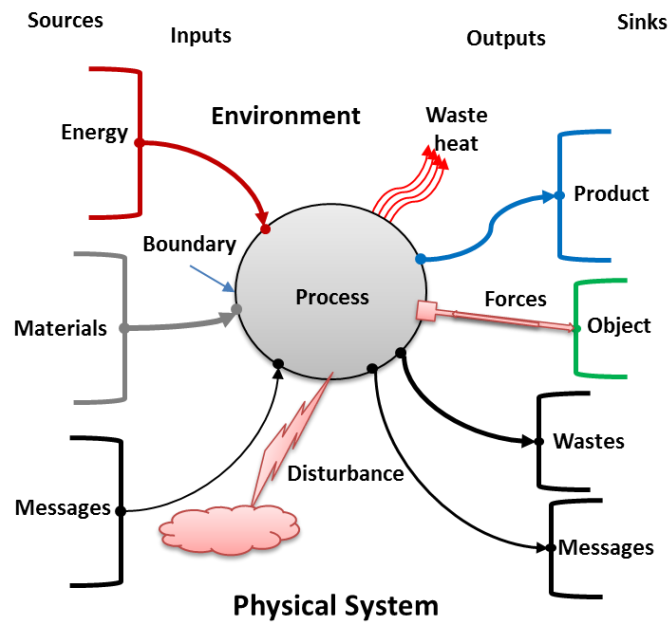


Fig. 1.2. This is an abstract representation of a generic 'real' physical system. It is called a 'process' because it receives inputs from its environment and does physical work on them to produce 'product' outputs along with wastes (material and heat).

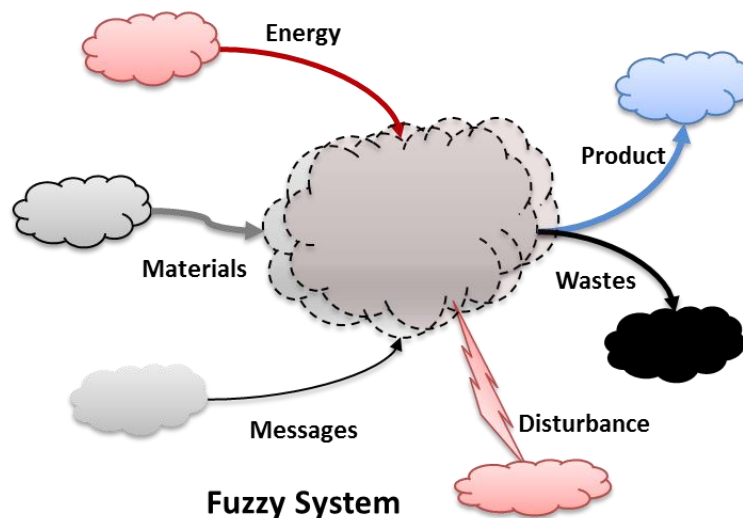


Fig. 1.3. When considerable uncertainty or ambiguity limits the capability for defining a system or its environment then it needs to be considered as "fuzzy."

Real physical systems are the objects of study of the sciences and engineering, as defined broadly in footnote 1. They are real in the sense that they exist. They are physical because they are experienced via sensory perceptions or the senses via augmentation with instrumentation. The act of studying a physical system is accomplished with abstract systems such as the various symbols and names used in figures 1.2 and 1.3. Other abstract systems, such as mathematics, are used to describe the attributes, relations, and dynamical behaviors of those concrete systems.

1.2.2 Systems that Seem Ephemeral

In the introduction mention was made of abstract systems contrasted with concrete systems which are real, physical objects in the world. The term ‘ephemeral’ is used here to suggest that abstract systems do not seem to have a physical embodiment. Indeed, abstract systems are often treated as if they do not. But in reality, such systems do have a form of physical embodiment at times, for example when your brain is thinking about a concept or a simulation model is instantiated in a computer memory.

The term ‘abstract’ does not mean that a system might be unembodied. Rather it means that the system has been representationally reduced to a set of parameters (e.g. variables) and mechanisms (e.g. functions) that can be computed either by brains or by computers producing results that resemble the real system. The ultimate abstraction is the naming of something (nouns), or some relation (preposition), or some action (verb) so that they are highly compressed for communications. Such abstractions have to have corresponding representations in the brain or computer memory that can generate an expansion to a less abstract version of the system.

1.2.2.1 Systems in the Mind

This specifically refers to mental models or conceptual models. That is, they are models of real or imagined systems that operate within the human brain¹⁵. Systems in the mind are instantiated in strongly interacting networks of neural clusters in the neocortex. When you see that house down by the lake with the red roof, your brain is activating circuits for a huge number of concepts, house-ness, redness, lake-ness, nearness, and so on. Each of these contains multiple subsystem concepts. For example, the house concept includes walls, roof (which is connected to the redness concept), doors, windows, etc. Each of these in turn is linked to concept clusters for more details, like texture of the siding or roof, shade of red, and so on. All of the features that constitute the scene are activated in multiple areas of the cortex, but are linked by mutually excitatory axons that reinforce all of the subsystems and sub-subsystems to activating in what is now called “working memory,” the aggregate of percepts and concepts that are currently active.

¹⁵ Would that there was space permitting a foray into the mind/brain arguments that dominate the psychology/neurology/philosophy worlds. We will not go that route. Here we simply claim that mental states and experiences (subjective) are the product of neurological processes, of clusters and networks of neurons working together to “represent” concepts in working memory that are, in turn, linked to abstraction concepts (words) that are processed sequentially to produce language.

1 If this collection of percepts and concepts are consistently activated on multiple occasions
2 they will be consolidated into another cluster of neurons (generally located further toward the
3 front of the brain) that effectively code for the abstract concept, as discussed above, it is given a
4 name. The latter is a long-term encoding of the house by the lake with the red roof instance. And
5 when your mind recalls this cluster by activating it (for whatever reason), it, in turn, activates all
6 of the perceptual and conceptual clusters that previously activated together when you were
7 actually seeing the object and its environs.

8 This is a very brief description of an extremely complex process that goes on in the brain to
9 represent systems in neural networks that can be formed “on-the-fly” and if properly reinforced
10 can become permanent memories. The main intent here is to show that the brain is very much
11 able to record and use systemness in how it models the real world. It has the additional great
12 ability to experimentally put multiple concepts together in ways not encountered in the real
13 world naturally, like unicorns. This is the basis of our ability to invent tools and stories.

14 **1.2.2.2 Systems in Symbolic Text**

15 We invented the ability to represent mental models or images in symbols and icons. We can
16 write down a sequence of symbols that represent, even if arbitrarily mapped, our spoken
17 languages. Once the conventions of the mapping are agreed upon among participants, we can
18 start recording and recalling systems that are etched into an appropriate medium. We can write
19 and read sentences so that the systems in our minds can be conveyed not only by spoken words
20 but by the conveyance of the media itself. A message written on a piece of papyrus that
21 designates farmer Ahab as owning 13 jars of wheat in the granary records a system relation
22 between the farmer Ahab and the jars of wheat and the granary. That piece of papyrus could just
23 as easily be given to another person in order to transfer the claim for the 13 jars under Ahab’s
24 mark to another person.

25 Language captures descriptions of systems in the mind, which in turn capture systems in the
26 world. But language is a very fuzzy system. Words and sentences can be ambiguous. They can
27 mean slightly different things to different participants in a conversation.

28 In order to circumvent the problems with simple language descriptions, scientists and
29 engineers have turned to structured texts with well-defined terms. For example, engineers
30 employ standardized forms called “specifications” along with diagrams to convey descriptions
31 that are readily understood by anyone who is knowledgeable in the standard. The collection of
32 texts and diagrams are a system for expressing a concrete system.

33 Mathematics is a step further in abstraction but also in disambiguation. For example,
34 measurements of system attributes, by reliable measuring devices, can be represented much less
35 ambiguously in numbers. Moreover, relations between attributes (and their numeric
36 representations) can be highly unambiguous. Mathematics (and its sister, logic) still depend on
37 symbolic representation, but the symbols chosen are generally quite crisp. The relations can be

1 represented in operation symbols that have unambiguous meaning. Through operations of
2 deduction one can prove a sequence of applied operations always produces a particular and
3 specific outcome.

4 When we are trying very hard to be careful and precise in our meanings we turn to
5 mathematics and logic.

6 It is important to recognize that categories of mathematical symbols belong to an abstract
7 system. It is also important to realize that this is a static system as long as the symbols live only
8 on paper. In order to be dynamic (to prove new theorems, for example), it is necessary for the
9 systems to be encoded again into the minds of people who can then manipulate those symbols
10 according to the rules of behavior adopted for the particular system.

11 **1.2.2.3 Systems in Computers**

12 Combining text, graphics, and mathematics it is now possible to construct system models in
13 computer memories and to simulate the dynamics of the system. Computer simulations of many
14 different systems are now quite common and in fact indispensable in modern technology,
15 governance, management, and sciences in general. We will have a considerable amount to say
16 about this approach to abstract systems in Part 3.

17 **1.2.3 Systems Equivalencies**

18 Each type of system is characterized by its location in the sense that each type exists in a
19 different medium. Even so there is a form of equivalency between them. That is a system in the
20 world is represented as a system in the mind and, in turn, is represented as a system in text, or a
21 system in a mathematical object with its rules of transformation. That mathematical system can
22 be represented (or converted) to computer codes. The system in the world is ultimately reduced
23 to a system in a computer memory.

24 Figure 1.4 shows a diagram of this equivalency between systems as represented in different
25 media. It is an extended version of the treatment in Mobus & Kalton (2015), chapter 1.

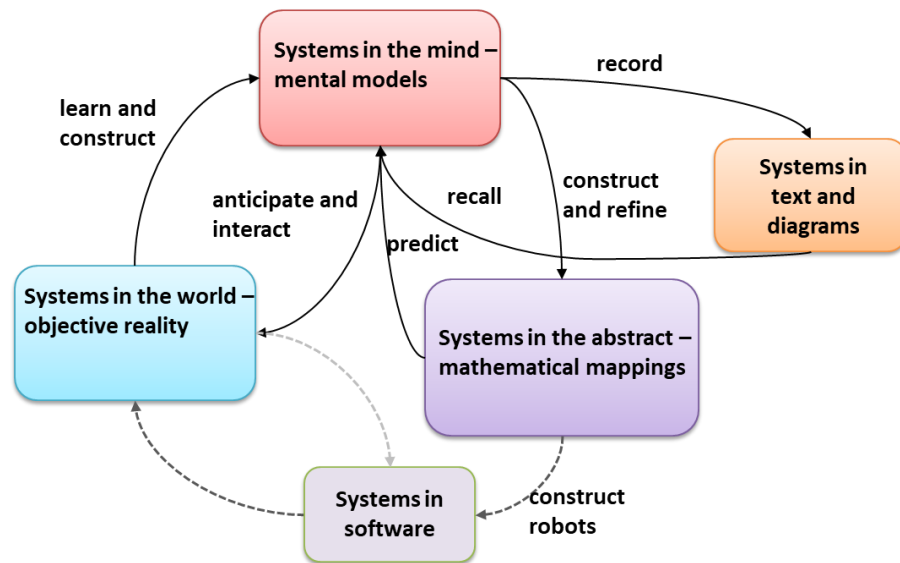


Fig. 1.4. Systems can be found represented in different media. After Mobus & Kalton (2015), figure 1.1 with addition of systems in text.

Systems located in other media, e.g. in mental models, are just as real as what we ordinarily think of as systems in the world (out there). As explained in Mobus & Kalton (2015), mental models are actually physical embodiments of abstract systems in neural tissues! Concepts are encoded in brain engrams, patterns of activation in neural clusters across the neocortex. These encodings, when activated in working memory have all of the physical characteristics of physical systems as described above. Moreover, as we will explain in the next chapter, these physical embodiments of concepts constitute a symbol system. The brain's design imposes a syntax on how such symbols are processed as thoughts and to expression in language.

In a similar way we can argue that systems encoded in mathematical formalisms only take on a life (have dynamics) when being active within the brain of a mathematically astute person. The mathematical formulas are, after all, concepts within the brain encoding mechanisms and thus, too, become real physical systems. The same argument applies to systems in text. A mind constructs the language equivalent of a system being described (see chapter 3 for a full explanation) and records it in text. Another mind can read and interpret the text constructing a mental model of the system that then, once again, becomes a real physical system in neural tissues.

If a system can be translated to a mathematical representation it can be translated into computer codes and run as a simulation in a computer memory. As with representations operating in a brain, being thus real physical systems, a system being simulated in a computer has all of the same attributes of a real physical system too.

There are, of course, significant differences in terms of systems themselves, as they are in the real physical world, and systems represented in the other media. Systems in other media are

only models or abstractions of the real systems. They suffer from ‘loss of information’ in being reduced to representations. Mental models are probably the least ‘reduced’ because of the way the human brain can encode the representations – being able to represent levels of detail as needed to make judgments and predictions about the real system’s behaviors.

What we want to emphasize here is that all of the various supposed ephemeral kinds of ‘systems’ are, in reality, real physical or concrete systems when one considers that their only real life is either in a brain or in a computer memory and simulation. They all require organization, boundaries, inputs of matter and energy and output behaviors and wastes when in brains or computers (e.g. waste heat). When systems are recorded as text or mathematical formulas those recordings are passive representations. When concepts in the brain are not brought into working memory, they too are just recordings waiting to be brought to life. But while alive, they are as subject to the principles of systems as any so-called real physical system.

1.3 Principles of Systems Science Reviewed

The term ‘principle’ is used here in its sense of a regular consequence of nature operating according to laws. For example, in nature, at all levels of organization from fundamental particles up through super clusters of galaxies the bits (like atoms) have tendencies to come together (be it the strong force or gravity) or be forced apart. They have “personalities”, like valence shells in atoms that may either be attractive or repulsive. It doesn’t matter if we are talking about real atoms (elements) or people, or societies. Each of these has characteristics that either facilitate interactions or cause repulsion. In the former case some new, higher order structure with emergent properties and/or behaviors comes into being. The principles invoked here are: 1) formation of networks of components, 2) hierarchical structure, 3) complexity increase, and 4) dynamics resulting from new configurations (constraints and degrees of freedom). But these are just the obvious ones. In systems science we learn that all of the principles may be at work at once.

In Mobus & Kalton (2015) we identified twelve basic principles that apply variously to all systems¹⁶. Some apply more to very complex systems, but all twelve apply to the most complex ones. Here is an abbreviated list of the twelve principles covered in Mobus & Kalton (2015).

1. Systemness: Bounded networks of relations among parts constitute a holistic unit. Systems interact with other systems, forming yet larger systems. The universe is composed of systems of systems.
2. Systems are processes organized in structural and functional hierarchies.

¹⁶ We neither claimed that these were all of the major principles nor even that they were THE major principles, only that they seemed to capture what we felt was the spectrum of systems science. In addition to these twelve ‘major’ principles there are numerous sub-principles, some of which we explicitly identify in various chapters in the book.

3. Systems are themselves, and can be represented abstractly as, networks of relations between components.
4. Systems are dynamic on multiple time scales.
5. Systems exhibit various kinds and levels of complexity.
6. Systems evolve to accommodate long-term changes in their environments.
7. Systems encode knowledge and receive and send information.
8. Systems have governance subsystems to achieve stability.
9. Systems contain models of other systems (e.g. simple built-in protocols for interaction with other systems and up to complex anticipatory models).
10. Sufficiently complex, adaptive systems can contain self models.
11. Systems can be understood (a corollary of #9) – Science.
12. Systems can be improved (a corollary of #6) – Engineering.

Below we provide brief descriptions of these as they appeared in that prior book as a review or to provide some background explanations. These principles will be used throughout this book as the basis for various methods, but particularly for the whole enterprise of understanding real systems.

Figure 1.5 organizes these principles according to relations between them. Evolution is the overarching principle that determines the long-term unfoldment of the other principles. The core principles apply to even simple systems. The operational principles apply to all systems but in simple systems are not as readily identified. Since this book relates to understanding very complex systems all of these twelve will apply.

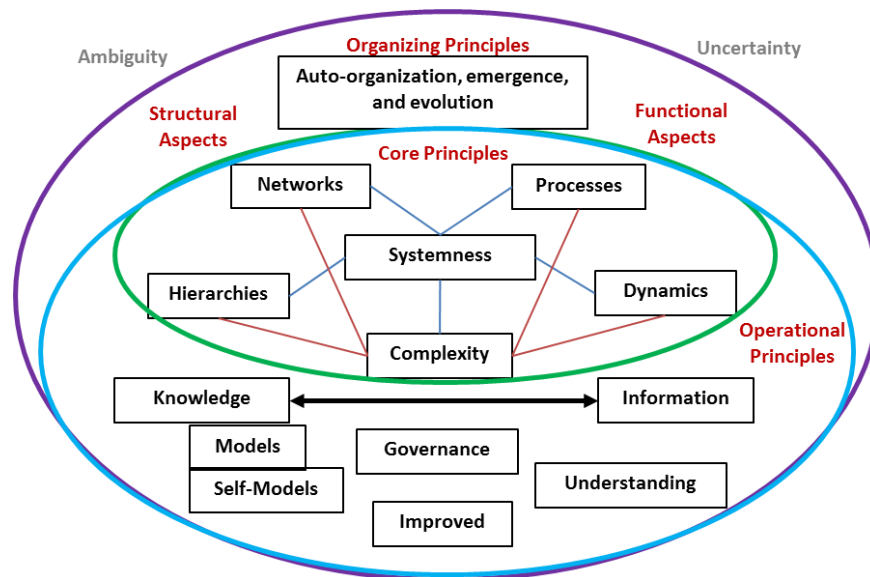


Fig. 1.5. A system of system science principles

The purpose of having a set of principles that apply to systems in general is so that we know what we are looking for when we analyze a system of interest (SOI).

A note on principles 11 and 12: These are couched as corollaries to principles 9 (models within systems) and 6 (evolution). They are special cases of the lower numbered principles. In humans, mental models of the things in the world are what we mean by understanding (in principle). For intentional agents, like birds that build nests or humans that design spacecraft, the system in which they operate can be evolved (improved) for a purpose. This latter case will occupy a fair portion of this book.

The rest of this section is borrowed from Mobus & Kalton (2015, chapter 1)¹⁷ to provide readers with an introduction to the main principles we introduced there. In each subsection title we include the chapter reference in Mobus & Kalton (2015) as “M&K Chapter(s) *x*,” where *x* is the chapter number.

1.3.1 Principle 1 – Systemness (M&K Chapter 1)

As shown in figure 1.3, this is the *core of the core principles*, meaning that it is connected to all of the other principles. This principle asserts that everything observable in the Universe is a system and establishes the idea that the core principles are to be found at every scale of space and time in one form or another.

The observable universe is a system containing systems¹⁸. Every system contains subsystems, which are, in turn, systems. The Universe may be the only instance of a closed system which establishes the upper bound on systemness. If Smolin (1997) and others postulating “Loop Quantum Gravity” (LQG) are correct, then “monads” existing at Planck scales of time and space may be the smallest objects that meet the qualifications of systemness¹⁹. It is possible to imagine monads as the smallest entities that qualify as systems (i.e. have inputs and outputs and interrelations with other monads), and, hence, provide the lower bound on systemness. All things that humans observe between these two extremes, from Planck scale to the “size” of the whole Universe, are systems (see Chapter 2, An Ontological Framework).

Systems of all kinds are found to be composed of components, which may themselves be subsystems (i.e. systems in their own rights). Systemness is a recursive property in which, starting at any arbitrary mid-level scale, one can go upward (seeing the initial system of interest as a subsystem of a larger system) or downward (analyzing the components and their interrelations²⁰). This principle guides both analysis, in which systems are understood by

¹⁷ These paragraphs are quoted from Mobus & Kalton (2015) but have some additional information not in the original. No attempt to identify such has been made as it seems immaterial to the intentions of this book.

¹⁸ Smolin (1997), Primack & Abrams (2006).

¹⁹ Monads are “entities” invented by the late 17th, early 18th century German philosopher, mathematician and physicist Gottfried Leibniz who posited them as the simplest objects of substance. Smolin relates monads to strings in string theory. See: <https://en.wikipedia.org/wiki/Monadology> for a description of Leibniz’s original ideas. See Smolin (2004) for ideas re: LQG, also: https://en.wikipedia.org/wiki/Loop_quantum_gravity.

²⁰ One might think there is a potential problem with infinite regress in this definition. We address this in Principle 2 and later in the book. There are reasonable stopping conditions in both directions of analysis. Practically speaking, however, most systems of interest will not require approaching those conditions.

breaking them down into components and the functions of components, and synthesis, in which the functioning of systems is understood in terms of their place in a larger relational web.

For our purposes, we will not be much concerned with the very largest scale (cosmology) of the Universe, nor the very smallest scale of the presumptive monads of LQG. But every scale in-between that we can observe will be fair game for understanding systemness.

1.3.2 Principle 2 – Systems are Processes Organized in Structural and Functional Hierarchies (M&K Chapter 3)

Since all components and their interactions exist only as processes unfolding in time, the word “system” and the word “process” are essentially synonymous (see Chapter 2). We often use the word when wishing to denote a holistic reference to an object considered as an organized relational structure²¹. When we use the term we are usually denoting the internal workings of an object that take inputs and produce outputs. Even systems that seem inert on the time scales of human perception, e.g., a rock, are still processes. It is a somewhat different way to look at things to think of rocks as processes, but at the atomic/molecular scale inputs like water seepage, thermal variations, etc. cause the component molecules and crystals to change. The rock’s output, while it still exists, is the shedding of flakes (e.g. of silica) that end up as sands and clays in other parts of the environment. So, in order to understand the organized structure of the earth, the geologist must study it as process, not just structure!

A hierarchy is a layered structure in which the lowest layer is constituted of the simplest components in the structure, and usually the numbers of components is large compared with other layers. In general, also, the time constants for dynamics of layers lower in the structure are much smaller, i.e. things happen faster. The next higher layer consists of subsystems composed of components from the lower layer in which component interactions within the subsystem are stronger than interactions between components in other subsystems. The subsystems have effective boundaries or concrete boundaries. This layering and the composition of subsystems taken from the next lower level is usually represented by a tree structure (in the graph theoretic sense, see Chapter 3, Figure 3.6 for an example).

The hierarchical nature of system structures has long been recognized (Simon, 1998; Koestler, 1967). As process, functional hierarchies correspond with the structural hierarchical architecture of systems. Hierarchies are recognized as the means by which systems naturally organize the work that they do as a response to increasing complexity (the increase in the number and kind of components at any one level in the hierarchy). Analytical tools that decompose systems based on these hierarchies are well known, especially in reductionist science. But also when we attempt to construct a system that will perform some overall function for us, we find it

²¹ Arthur Koestler (1905-1983) used the term ‘Holon’ to describe this fundamental structuring of a whole composed of parts that are themselves wholes. He used the term ‘Holarchy’ to refer to the hierarchical relation between the system as a whole and its subsystems. See: Koestler (1967).

is best to design it as a hierarchy of components integrated into working modules, which, in turn, are integrated into meta-modules. The notion of hierarchy will become especially important when we take up the question of coordination and control in our discussion of cybernetics.

1.3.3 Principle 3 – Systems Are Networks of Relations among Components and Can Be Represented Abstractly as such Networks of Relations (M&K Chapter 4)

Systems are networks of components tied together via links representing different kinds of relations and flows. This principle ties several other principles together. Namely, Principles 9 and 11 have to do with how we can create models of systems in the world with systems in the mind, or systems in the abstract. The emerging network science (Barabási, 2002) provides us with a range of formal tools for understanding systems. For example, graph theory, in discrete mathematics, provides some powerful tools for examining the properties of networks that might otherwise be hidden from casual observations.

For example, Figure 1.6 shows the existence of a node type, the hub, that was not understood until the application of network theory to several example networks. A “hub” is a node that is strongly connected to many other nodes in such a way that it provides a kind of bridge to many other nodes (depending on the direction of connectivity – the two-way connections in this figure represent the more general case).

Another powerful way to use graph and network theories, very closely related to one another, is the “flow graph”, also called a “flow network.” In a standard graph, the links represent relations and directions of influence. In a flow graph the links show a single direction of influence but the influence is carried by a flow of a real substance, i.e. matter, energy, or informational messages. In these cases, the rate and magnitude of the flow are considerations and need to be represented in some fashion. Typically, we use numeric and textual labels to identify those flows. More abstractly, as in Figure 1.6, they can be represented by the thickness of the arrows showing direction.

These kinds of graphs, and the networks represented have been used to analyze so many kinds of systems to date, that they have become an essential tool for the pursuit of systems science. Grounding in network and graph theoretical methods is thus very helpful. Even if the quantitative methods of graph theory are not fully made explicit, it is still an invaluable conceptual tool to know how to qualitatively characterize systems as networks of interacting components and to provide detailed descriptions of the nature of the links involved in order to provide a “map” of the inner workings of a system.²²

²² The relationship between a network and a map should be really clear. The word “map” is used generically to refer to any graphic representation of relations between identified components. A map of a state or country is just one example of such a network representation, as the network of roads that connect cities, etc.

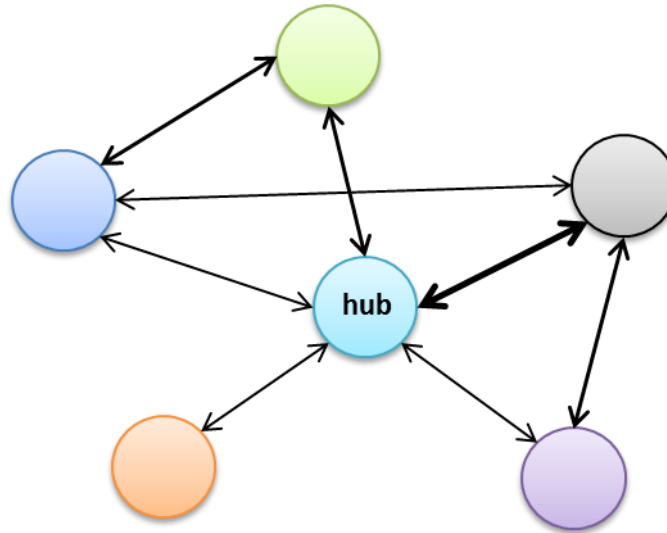


Fig. 1.6. A network of components (nodes) can abstractly represent interrelations by links (edges) in a graph structure. Interaction strengths are represented by arrow thickness, but could be represented by numerical labels. This is a bi-directional graph meaning that the relation goes both ways, e.g. like electromagnetic force. In this graph the node labeled “hub” is connected to all other nodes, so it would be expected to play a key role in the functional dynamics of this network.

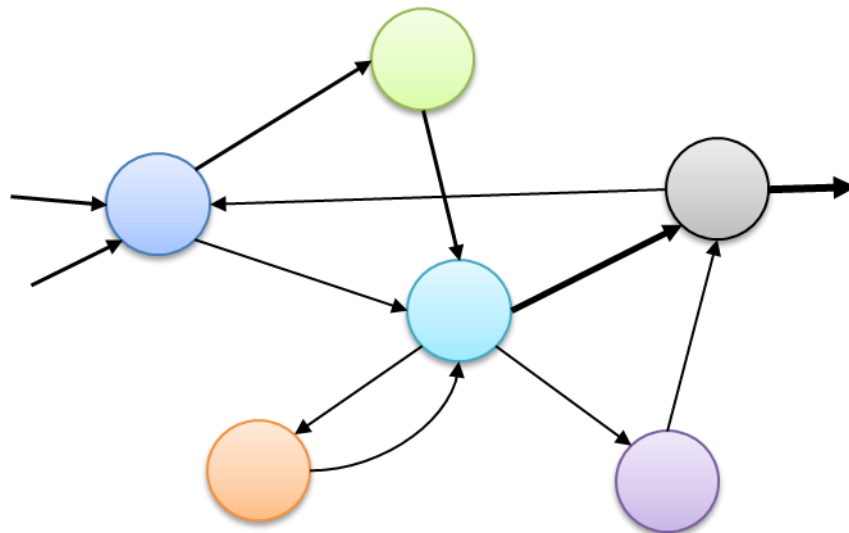


Fig. 1.7. The same network as represented in Figure 2 is here represented as a “flow network”. The arrows are unidirectional indicating that the net flow is toward the node with the arrow point. Flow networks provide additional mathematical tools for analyzing the dynamics of a system. Here we have added inputs and outputs in conformance with the idea that such a network is a process with an overall function (outputs given inputs). Again the “volume” of a flow is indicated by the thickness of the arrow for simplicity.

1.3.4 Principle 4 – Systems are Dynamic Over Multiple Spatial and Time Scales (M&K Chapter 6)

Dynamics (or overt behavior) refers to how the processes operate or change inputs into outputs over time. In the most general sense, the lower the level of resolution in space dimensions, the smaller the resolution in time scales relevant to dynamics. At very small spatial scales (e.g. molecular) such processing proceeds in the micro- and millisecond time scales. At somewhat larger spatial scales, say at the level of whole cells, the time constants might be given in deci-seconds ($1/10^{\text{th}}$ of a second). On still larger spatial scales processes might be measured in seconds and minutes. On geological spatial scales geophysical processes might be measured in centuries or even millennia. What about the Universe as a whole?

We sometimes find that critical processes that operate over sufficiently different time scales can have hidden negative consequences for the system as a whole. Systems constantly adjust themselves by feedback loops, but when interdependent components operate with feedback loops of different temporal scales the system may become unstable.²³ In understanding what goes wrong and leads to disruption and collapse of function in natural and human built systems, we generally find dynamical mismatches at the root. For example, the fast economic payoff for clear-cutting forests or harvesting fish by factory trawlers is not in itself scaled to match the reproductive cycles of trees or fish. Systems science explicitly calls for attention to dynamics at all time-scales in which conflicts could threaten the sustainability of the system. In those cases where sustainability is desirable, we look for ways to find “harmony” among the different levels of system composition (the hierarchy).

1.3.5 Principle 5 – Systems Exhibit Various Kinds and Levels of Complexity (M&K Chapter 5)

Complexity, like network science, is really one characteristic of *systemness*. But since the complexity of systems is a critical attribute in understanding why a system might behave as it does or fail to behave as might be expected, complexity science has emerged as a subject standing on its own (See Mitchell, 2009). Chapter 5 in Mobus & Kalton (2015) discusses the nature of complexity in more detail. Specifically, we have adopted the view expressed by Herbert Simon (1998) that complexity is a measure derived from several attributes of system structure. Systems are described as hierarchically organized networks of strongly interacting modules at any level in the hierarchy. Each module is, itself, also a subsystem and thus a hierarchically organized network of strongly interacting modules. That is systems are nested structures. This structure is repeated down to a level where we recognize what we will call atomic components (see chapters 2 & 3). Ultimately the complexity of any identified system is

²³ For an extensive analysis of the dynamics of development and collapse in human and natural systems, see. Gunderson and Holling (2002).

1 based on the total number of components, number of kinds of components, and the attributes of
2 networks within a level and between levels (i.e. the degree of modularization).

3 For our purposes we adopt this intuitive definition of complexity. A full explication of
4 complexity would require a full volume on its own. Numerous other authors have tackled the
5 problem with varying degrees of success. Most of modern complexity science has focused on
6 several interesting phenomena in which various systems demonstrate complex behavior in spite
7 of their particular dynamics being based on relatively simple rules. These views of complexity
8 are important when considering the generation of complexity in real systems, but we maintain
9 that the final manifestation of complexity is embodied in the structures and functions of the
10 systems themselves. Understanding the generative functions that give rise to complex structures
11 is clearly needed (see Chapter 2) but not the same as an index measure of the complexity of a
12 system.

13 Later, when we consider the transformation and evolution of systems (Chapter 2), we will
14 see that systems become more complex by virtue of broadening and deepening the hierarchy and
15 new functionality and unexpected potentials may emerge. But complexity also carries a price:
16 some of the more important findings in complexity science, such as deterministic chaos, self-
17 organized criticality, and catastrophe theory, have shown us that complexity and non-linearity
18 can, themselves, be sources of disruption or failure.

19 Human societies and institutions present one of the most trenchant examples of the trade-
20 offs of complexity. Joseph Tainter (1988; also Tainter & Patzek, 2011) has put forth a very
21 credible argument that as societies become increasingly complex as a result of trying to solve
22 local problems, only to create bigger problems, the marginal return (e.g. in stability) decreases
23 and even goes negative. This phenomenon is linked with the collapse of many historical
24 civilizations (Scott, 2017), such as the Roman Empire, and causes some social scientists today to
25 voice concerns regarding the trajectory of our modern technological civilization. This aspect will
26 be important to keep in mind when we discuss the issues of governance of complex systems.

27 **Note for Principles 6-12** The following principles, those outside of the core principles in
28 Figure 1.5, apply mainly to more complex systems, especially those described as “complex
29 adaptive systems” (CAS). The meaning of this term will be made clear later.

30 **1.3.6 Principle 6 – Systems Evolve (M&K Chapters 10 & 11)**

31 In many ways this principle, shown in a box under “Organizing Principles” in Figure 1.3, is
32 itself composed of several sub-principles and is the most overarching of them all. Indeed, it can
33 be reasonably argued that the complexity of the systemness we find in the universe is an outcome
34 of evolution. All systems can be in one of three situations. They can be evolving toward higher

organization, maintaining a steady-state dynamic²⁴, or decaying. The principle that systems evolve is based on the systemic effects of energy flows. If there is an abundance of inflowing *free* energy, that which is available to do useful work, then systems (as a general rule) will tend toward higher levels of organization and complexity (see Principle 8 below). Real work is needed to maintain structures and to create new, compound structures. When the energy flow is diminished, the Second Law of Thermodynamics (entropy) rules, and instead of the uphill climb to higher order and complexity or the energy-demanding maintenance of complex order, a process of decay sets in and systemic order deteriorates towards random disorder.

1.3.7 Principle 7 – Systems Encode Knowledge and Receive and Send Information (M&K Chapters 7 & 8)

Information and knowledge are most often thought of as pertaining to systems in the mind, a subset of systems. Another way of looking at it, however, finds them in the operation of all systems as they move into a future with possibilities already shaped by the present state of the system. This approach usefully grounds knowledge and information in systemic structure, which not only *is* as it is, but *means something* for any possible reaction to events as they unfold. That is, the system by its very structure “knows” how to react. From this foundation in physics, we will be able to more clearly trace the emergent systemic differences in modalities of knowledge and information as biological and psychological life evolves from the original matrix of physical and chemical systems. This will allow a more careful differentiation of the mental way of possessing knowledge and processing information from the physical way, making it clear that the way living organisms hold knowledge and process information is a more complex, evolved form of doing something every system does. The subjects of information and knowledge and their duality will be discussed in Chapter 2.

1.3.8 Principle 8 – Systems Have Regulatory Subsystems to Achieve Stability (M&K Chapter 9)

As systems evolve toward greater complexity the interactions between different levels of subsystems require coordination. At a low level of complexity, cooperation between subsystems may emerge as a matter of chance synergies, but more complex systems need more reliable mechanisms of control to coordinate the activities of multiple components. Thus control, typically exercised through feedback processes linked with specialized subsystems, becomes an important issue in any discussion of the function of both fabricated and evolved systems. When we take up cybernetics in Chapter 11, we will see how complex logistical coordination is achieved through the development of control hierarchies (multiple controllers require another layer of coordination among themselves!). And then the question will reemerge in an even more challenging form when we discuss the reproductive ability that marks the emergence of life,

²⁴ Steady-state does not imply a constant level of some measure. Steady-state systems may as readily be characterized by statistical properties that are stationary but not static.

where not just coordination but accurate copying of the entire system pushes the control question to new levels.

1.3.9 Principle 9 – Systems Can Contain Models of Other Systems (M&K Chapters 8 & 13)

We are all aware of the function of mental models, how the image of how someone looks aids in meeting with them, how the map modeling the street layout enables us to navigate the city, or how the blueprint guides the construction of the building. But modeling occurs not just with minds, but in all sorts of systemic relations where one system or subsystem somehow expects another. Thus a piece of a puzzle models inversely the shape of the piece that will fit with it, and in a similar way, molecules, by their shape and distribution of charges, model the molecules with which they might interact. In general, systems encode in some form models of the environment or aspects of the environment with which they interact, though this modeling element of functional relationships is realized in many different ways and levels in different sorts of systems.

1.3.10 Principle 10 – Sufficiently Complex, Adaptive Systems Can Contain Models of Themselves (M&K Chapters 7, 8, 9 & 13)

Adaptive systems such as living organisms can modify their models of an environment to adapt to changes, or simply for greater accuracy (i.e. learning). Creatures capable of having mentally mediated roles and identities include models of themselves, and these likewise may involve greater or lesser accuracy. For humans, as we shall see, the intertwined models of the world and of themselves become structured into their societies and inform the way societies interact with the environment. Systems science reveals the dynamics by which such models are shaped, and supplies a framework within which to critique their validity. Insofar as inaccurate models contribute to dysfunctional interaction between society and the environment, systems science thus offers an especially valuable window on the question of sustainability

1.3.11 Principle 11 – Systems Can Be Understood (A Corollary of #9, M&K Chapters 12 & 13)

As discussed above, science is a process for explicating the workings of systems in the world, and it has very recently been turned to a better understanding of systems in the mind as well. It has moved our understanding of these systems to new levels by employing formal systems in the abstract. As these formal systems mature and are fed back into mental models arising from experience, we humans can develop better understanding of how things work both in the world and in our own minds. We will never reach an end to this process of understanding systems and some levels of systems may continue to elude us, but in principle systems function in terms of relational dynamics, and this is an appropriate object for human understanding.

1 The reason we call this principle a corollary of Principle 9 is that the understanding comes
2 from the efficacy of the models we hold of the systems we study. Science is the paradigmatic
3 example. As a social process, science seeks to characterize and model natural phenomena by a
4 piecewise approximation process. The models are improved in terms of accuracy and precision
5 as well as predictive capacity over time. Models are sometimes found to be incorrect and so are
6 abandoned in pursuit of better models. Alchemy evaporated as chemistry arose. In the end,
7 efficacy is the test of the explanatory power of the models. This is what is meant by
8 ‘understanding’ something. When you understand you can make predictions, or at least project
9 scenarios that can then be tested. Then, the accuracy, precision, and explanatory power of the
10 models can all be assessed and, according to Principle 8, using information feedback for self-
11 regulation, the models can be further improved (or found wanting and abandoned).

12 The human capacity to learn, especially in abstract conceptual models, is an individualistic
13 form of Principle 11. Whereas science builds formal models in the abstract (and increasingly in
14 software), we individuals construct knowledge in our neural networks. Knowledge is just another
15 word for model in this sense. Our brains are capable of building dynamic models of systems in
16 the world and using those models to predict or spin scenarios of the future state of the world
17 given current and possible conditions. We have a strong tendency to anticipate the future, and in
18 so doing we are relying on subconscious models of how things work in order to generate
19 plausible explanations, both of what has happened and what might happen in the future. When
20 we say we learn from our mistakes we are, just as in the case of science, correcting our models
21 based on errors fed back to our subconscious minds where the construction takes place.

22 When we say that systems can be understood, then, we are referring to our ability to
23 function successfully through the guidance of models in the mind that correlate with relevant
24 features of systems in the world. A model is not identical with the object it models, so our
25 understanding of a system is not identical with the system itself, and therefore is never final. A
26 given model can always be carried further, and another perspective yielding an alternative model
27 is always possible. And this takes us to our twelfth and final principle.

28 **1.3.12 Principle 12 – Systems Can Be Improved (A Corollary of** 29 **#6, Chapter 12)**

30 If one has the boldness to assert that something is an improvement, they are likely to meet
31 the familiar counter, “Who’s to say?” If I say it’s great to have a new highway, someone else can
32 always bring up sacrifice of land, air quality, noise, or others of a virtually unlimited (and
33 equally systemic) number of ways in which the improvement might also be considered a
34 degradation. Systems science will furnish a framework for thinking through these issues.
35 Principle 6 notes that, with available free energy, systems can evolve to higher complexity with
36 emergent new properties. But this is not to say the dynamics that ratchet up complexity
37 automatically lead to improvement. Quite the contrary, increased complexity can also lead to

1 instability and collapse. And then again, who's to say that in the big picture stability is better
2 than collapse?!

3 We will frame the systemic question of improvement in terms of function. Dynamic systems
4 in their operation necessarily produce consequences. This is their functioning. And in the study
5 of auto-organization and evolution we find that functioning changes as complexity increases.
6 But unless this causal functioning somehow *aims* at some result, all results are equal and the
7 notion of improvement has no basis, no metric. So a systems account of evolution will have to
8 take up the question of when and how causal functioning gets to the condition where the
9 operation of the system can be observed *to aim* selectively at some kind of result. Although aim
10 is hard to identify in the pre-life universe, the world of life is full of such processes. How then
11 does evolution ramp up to start working in terms of *improved* function, the selection of the
12 fittest?

13 We, our metabolisms, and the entire world of life operate and organize in an ongoing
14 process of looking for what fits and better fits our varied aims and purposes. And of course all
15 those aims and purposes are not perfectly harmonized, as both individual lives and whole
16 systemic sectors intersect with vectors that include tensions, competitions, and sometimes
17 outright contradiction. The success of the predator is the failure of the prey. So with a narrow
18 focus one can improve either the hunting of the predator or the elusiveness of the prey. At a more
19 inclusive systemic level, improvement would have to look for the best dynamic balance, since
20 too much success on either side, while good for the individuals involved, would have negative
21 consequences at the level of the species well-being. And improving an integral ecosystem in
22 which myriad intersecting competitions are woven into a dynamically shifting mutual fit would
23 be a yet more daunting challenge. And the same goes for social systems, where clarity regarding
24 individual lives or narrowly focused issues is much easier than the endlessly contested visions of
25 what constitutes an improved society.

26 1.4 Systems Science

27 Systems science is a meta-science. This is implied in section 1.1 and Figure 1.1. That is, it
28 crosses all of the traditional science domains to address patterns of physical reality that are found
29 in all of those domains. The examples mentioned above about attraction and the formation of
30 networks is as true for quarks, as for atoms, as for molecules... as for galaxies and everything in
31 between in terms of scale of space and time. Such patterns are found in physical systems,
32 chemical systems, biological systems, social systems, and large scale planetary systems (i.e.
33 biospheres, atmospheres, etc.). The objective of systems science is to explicate these patterns in
34 such a way that the knowledge of them can be applied in any domain to help the domain
35 specialist discover the patterns in their particular subject of interest. The principles of systems
36 science listed above are the starting points for aiding domain specialists do their particular brand
37 of science.

1 Systems science attempts to organize system knowledge in a rigorous, structured manner,
2 just as all sciences do for their domain knowledge. The principles given above are a first
3 (possibly clumsy) attempt to provide a starting framework for this effort. We will be refining the
4 use of systems science to understand the world in this book.

5 Systems *thinking* is a more informal way of thinking about the world systemically.
6 Everyone, to some degree or another, has intuitions about the workings of the world they live in
7 and observe. For some people this naturally includes understanding connections and interactions
8 – connecting the dots, as we say. It includes grasping how causal relations can be circular, how
9 feedback can drive the dynamic behavior of some systems. A few people have strong intuitions
10 that allow them to make good decisions about how to work with the rest of the world for
11 everyone's benefit. Unfortunately, not everyone does. Systems thinking comes in shades of grey.
12 People range from systems-oblivious to strong awareness that they are observing systems and are
13 part of a larger system. The objective of systems science is to make explicit what systems
14 thinkers know implicitly with the hope that doing so will improve the systems thinking of
15 everyone through education.

16 In the next chapter on Systems Ontology we will provide a small sidetrack on how the
17 human brain evolved to perceive systemness in the world. It is actually an expansion from
18 principles 9 and 10 regarding how a system (the brain) can contain models of other systems
19 (everything out there) including a model of the self (some portion of what's in here that gives
20 rise to the feeling of 'I')²⁵. In turn, this is related to principle 7 regarding information
21 (communications) and knowledge (models).

22 1.4.1 'Problems' to be Solved

23 Ultimately, we need strong systems thinking and the tenants of systems science in order to
24 understand the problems with which we contend. That understanding is mandatory because
25 sometimes what we think is a problem to be solved is not really a problem at all, not when
26 understood as part of a larger system in which it is embedded. For example, human societies
27 often find themselves faced with conflicts with one another. The problem to be solved is how to
28 destroy the enemy before they destroy us. In the context of the immediate cause of conflict this
29 might seem like a reasonable approach. We have enlisted the aid of scientists to invent more
30 destructive weapons. But to what end? When viewed in the larger context of history and the
31 Earth's natural systems our little wars are immensely destructive not just of the other guys but of
32 a lot of our environment and our own psyches. The real problem to be solved is the question of
33 why conflicts arise and what steps might be taken to avoid those situations. Historians and
34 sociologists, of course, grapple with such questions. But so far as I know have not done so using
35 the kind of systems analysis being described in this book, and usually not even strong systems
36 thinking.

²⁵ Damasio (2000)

1 It is ironic that many of the tenants of systems science emerged from the efforts of the Allies
2 and Germans alike in World War II. Concepts from cybernetics (control), information theory and
3 computing were germinated during the war. But so was the atom bomb. The global politicians
4 were caught in the worst form of non-systems thinking – not understanding how the world as a
5 whole is a system. The scientists employed were involved in domain-specific development. Yet
6 out of that a number of scientists, already sensitive to the ideas of systems were able to bring
7 many of those ideas together in a unified concept of systemness²⁶. Led by biologists like Ludwig
8 von Bertalanffy, and philosophers like Alfred North Whitehead, who grasped a vision of how
9 these newer concepts fit into general patterns of organization and dynamics, many of the
10 scientists and thinkers came out of the war effort with a realization that humanity had to literally
11 see the bigger picture if it was to survive the 20th century and beyond. Systems science emerged
12 from a wonderful collective effort among many great minds in the late 1940s and early 1950s²⁷.

13 And then something typical happened. After the war it was recognized that scientific
14 research had played a significant role in helping the Allies win. Vannevar Bush²⁸, a prominent
15 engineer who had been head of the U.S. Office of Scientific Research and Development (OSRD)
16 during the war, wrote an influential memo that recommended forming research funding agencies
17 that would direct money to research universities to support innovative research to keep the US
18 dominant in the world of science and technology. The National Science Foundation came out of
19 this idea. And academia was changed forever. When you dangle money in front of administrators
20 they come up with incentives to get the academics to play ball. That incentive was tenure and
21 promotion. In order to win tenure, young academics were encouraged to obtain grants to do very
22 specific research in their domains. Part of the problem was that this included getting published in
23 recognized journals within the specific domains. As a result of this emphasis on domain-specific
24 research (to keep your job and get promoted), systems science became disintegrated into
25 specialized subfields like complexity science, cybernetics, information theory, and so on. In spite
26 of the fact that each of these used the word ‘system’ extensively (because their subject matter
27 was obviously embedded in systems!) the various sub-disciplines became specializations just
28 like all of the other sciences.

²⁶ I will be using this term frequently even though you will not find it in any standard dictionary. Systemness is the collective properties of a ‘thing’ that make it a system. Specifically, things that have the properties covered as the ‘core’ principles above, as a minimum, display systemness. The term, ‘systemic’ refers to a property or situation that is part of a whole system, so it does not quite work to encapsulate the constellation of properties of a system. Another term that is sometimes used in the same way as systemness is ‘systemicity’. It too is hard to find (perhaps in some British-based dictionary).

²⁷ It is quite typical in books on systems science to venerate as many of the great minds who founded the discipline in this time period. In Mobus & Kalton (2015), we acknowledged many of these people as they figured specifically into one or another sub-discipline. However, in this book we will not be spending much time recounting where the various ideas came from and lauding the founders. It is not for lack of respect and gratitude; it is for space efficiency! Histories of systems science and the scientists who helped found the area can be found in Warfield (2006) among others.

²⁸ See the Wikipedia article: https://en.wikipedia.org/wiki/Vannevar_Bush

1 This situation persisted throughout the remainder of the 20th century and into the start of the
2 21st century. Those who continued on in the tradition of an integrated whole science of systems
3 found themselves on the periphery of academia. There were concerted efforts to keep systems
4 science alive – interestingly one of the most successful areas for systems science was in business
5 schools where management scientists recognized the benefits of systems thinking. But on the
6 whole, it remained fractionalized and the parts only loosely coupled.

7 That situation started to change in the latter part of the 20th century when technologies like
8 the Internet began to play a significant role in economic life. The impetus was complexity. Not
9 only were technologies getting extremely complex but the whole fabric of our social systems was
10 too. Globalization, enabled by computing and communications networks along with the
11 availability of cheap fuel for shipping goods, created an additional layer of complexity that made
12 it clear that the world really was a system. With the realization of how humanity was affecting
13 the ecosystems of the world and, in fact, the whole world with climate change²⁹, the notion that
14 disciplinary sciences could address our issues began to crumble.

15 The watchword of today is “sustainability.” People everywhere are asking what do we need
16 to do to solve our energy problems, our food security problems, our ecosystems and mass
17 extinction problems, and the list goes on. They are implicitly recognizing that all of these global
18 and massive problems are interrelated. Their implicit systems thinking is kicking in and they are
19 beginning to realize they need systems solutions³⁰.

20 Thus, it seems it is time to re-integrate the various sub-disciplines that make up systems
21 science and use this science to tackle problem solving in a systemic way. Systems engineering
22 will be the application of a holistic systems science to design. This book will walk the reader
23 through this process. We will apply holistic systems science to the understanding of complex
24 systems and the problems that they suffer so as to find holistic solutions – the kind that minimize
25 unintended consequences.

26 Note that while these complex global problems are an immediate and compelling reason to
27 employ formal systems science, it isn’t just problem solving in the defensive sense that compels
28 us to turn to systems science. Technological progress today comes from the integration of
29 systems that are comprised of subsystems, or what is now called ‘systems of systems’ (SoS). The
30 “smart power grid,” the electric power distribution systems that brings electricity from power
31 plants to our homes and businesses is being investigated as a necessary solution to upgrading the
32 current (quite antiquated) grid, to accommodate the intermittency problem with alternative
33 energy sources such as solar and wind power, and to improve the efficiency of electricity

²⁹ Many scientists are calling for a formal renaming of the current era (at least since the advent of the Industrial Revolution) from the Holocene to the Anthropocene due to the global geologically embedded effects of human activity. See the Wikipedia article: <https://en.wikipedia.org/wiki/Anthropocene>

³⁰ Science, 356:6335, April 21, 2017 is a special issue featuring articles on “Ecosystem Earth” in which many of these exact questions are prominently featured (Vignieri & Fahrenkamp-Uppenbrink, 2017, and related articles).

consumption at the end user. This grid will involve so much more than relays and wires. It will involve sophisticated computing and communications subsystems for coordination of distribution. The same is true for a large variety of progressive developments in man-made artifacts such as transportation, communications, and food production³¹. All of the most interesting developments, e.g. self-driving cars and trucks, involve significantly greater complexities as compared with late 20th century technologies. As such, and noting principles 5 and 6 in which we will find that unanticipated behaviors often emerge from very complex combinations of heterogeneous subsystems, using rigorous systems science to analyze these ‘solutions’ and model their behavior so as to catch these behaviors in advance of unleashing them on the world is becoming an essential part of engineering.

1.4.1.1 Complexity

Beyond any doubt the most obvious cause of social and ecological problems is the sheer complexity of our globalized civilization.

For example, according to Worldwatch Institute the average American plate of food has traveled between 1,500 and 2,500 miles from farm to consumer³². The number of steps in growing, transporting, processing, retailing, etc. are unbelievable. Or, how many people today can repair, or even tune up, their own automobile. Look under the hood of a modern car! Thirty years ago, it was still possible to do a certain amount of maintenance on one’s car. Fifty years ago, it was ordinary for people to service their automobiles or even repair much of the engine, transmissions, or bodies. Cars were simpler. There were no computer chips to deal with.

Today it is almost impossible to do any kind of project like Mt. Rushmore’s sculptures of four presidents. Why? Because the number of environmental impact studies that would need to be done make such an undertaking a non-starter (in recognition that we humans tended to destroy natural habitat in such projects)! In a sense this is actually progress. We humans will not be directly responsible for the demise of a species of fish or beetle just to satisfy some hubristic urge. But the complexity of regulations also inhibits projects that might not result in any degradation just because of the added expenses of doing the studies.

Then there are the stories of complex artifacts such as baggage handling systems in major airports that were catastrophic failures due to poorly designed and implemented software.

Software systems are among the most prominent forms of complexity in today’s societies. And the failures of software development projects are among the costliest results. However, the same root of the problem and the same sorts of project failures are found in many different works of human design. Below, in the section “What Goes Wrong” we provide a few more examples

³¹ It is true that many of these developments are in part driven by the need to address carbon pollution, but they are also desirable developments even if we didn’t have this climate change sword of Damocles’ hanging over our collective necks.

³² See: <http://www.worldwatch.org/globetrotting-food-will-travel-farther-ever-thanksgiving>

1 along with explanations of how failure to employ rigorous systems methodologies (based on
2 rigorous systems theory) lead to these problems.

3 **1.4.1.2 Material and Energy Consumption**

4 Every system receives material and energy inputs for processing to product and waste
5 outputs. If the system is in balance with its environment it means that the resources of material
6 and energy are available in sufficient quantities to meet the system's needs. It also means the
7 products and wastes will be absorbed by the environment (e.g. there are customers that use the
8 products, and sinks that can recycle the wastes) at the rates of production. Systems that grow
9 larger than their balance point (or what is called the carrying capacity of the environment) will
10 extract more resources than can be replaced (either recycled or renewed). They will dump more
11 product or wastes into the environment than can be readily absorbed, thus poisoning the
12 environment for themselves and other systems. We know this to be the case from empirical
13 studies of both natural and human systems.

14 Systems that continue growing beyond their natural limits also tend to waste or inefficiently
15 use the resources they extract so that they attempt to increase their extraction rate in order to
16 compensate. We humans are guilty on all counts with the consequences that we have severely
17 polluted our world and are depleting our resources more rapidly than they can be replaced.
18 Resource extraction and output disposal are systemic problems that involve not only our desires
19 for wealth and clean air, but a deep understanding of just what the carrying capacity of the whole
20 planet is relative to human consumption. We are just beginning to get a handle of these issues
21 and we hope that with the aid of systems science we will have a better set of tools with which to
22 do so.

23 **1.4.1.3 Governance for Sustainable Existence**

24 It is tempting to pronounce a newly understood principle to add to the list of twelve above.
25 However, it is possible to consider this as a sub-principle within Principle 8 – systems have
26 subsystems for regulating their behavior. The sub-principle is that systems serve a purpose
27 within their embedding supra-system. This means that the system, as a subsystem of the supra-
28 system (Principle 1 re: hierarchies of systems within systems) is strongly coupled with
29 (generally) multiple other subsystems from which they get resources and deliver products of
30 value to the others (who are 'customers'). The whole supra-system persists over time as long as
31 all of the interacting subsystems are doing their 'jobs.' And so long as that is the case the whole
32 supra-system and its subsystems are sustainable.

33 The notion of serving a purpose (i.e. producing products of use in the system) is behind the
34 evolution of internal regulation sub-subsystems that keep the subsystem doing the 'right' things.
35 Such systems that succeed in serving their purpose are 'fit' in their environments (the other

subsystems)³³. Another term for systems that have such internal regulatory or governance subsystems is ‘purposive.’ That is, they are motivated to behave in what appears to be a purposeful manner – that is they appear to have their own purposes. In fact, their purposes are just the dual of the purpose they serve. A good example of this is the role of a top carnivore in a food web. Their apparent purpose is to find and eat prey. In fact, they are serving the purpose of culling (returning a certain amount of prey biomass to the environment in the form of excrement that will be recycled by bacteria) and population control in the ecosystem. The governance system involved is a combination of internal drives within each individual carnivore coupled with feedback loops through the food web itself. If the carnivores cull too many prey, the latter numbers decline leading to less food for the carnivores and their numbers eventually also decline. The nutrients returned to the soil may boost primary production (plant growth) providing sustenance to a then growing population of prey animals. Finally, this increase in population means the predator population can start to recover.

Governance mechanisms involving a hierarchy of cybernetic sub-subsystems are what make possible subsystems like carnivores or businesses fulfilling their purposes, both their internal goal-directed purposes and their larger purpose within the whole supra-system. In Chapter 11, we will see how this works in more detail. We will also show how these mechanisms constitute the ideal of a distributed decision system. Even though we talk about a hierarchy of structure and function, this is not the same as a command-and-control version of governance.

Chapter 9 will go deeply into the nature of governance and management subsystems that are required for all complex adaptive (CAS) and complex adaptive and evolvable systems (CAES), which will be discussed throughout this book. Every such system is exposed to challenges from environmental changes to internal wear and tear or entropic decay processes that can produce substantially suboptimal behavior. Any such system must remain fit by compensating or adjusting for these challenges so that a central problem for them is the constant monitoring of the environment and self along with the decision processes and activation capabilities in place to maintain themselves in the face of these challenges.

This requires an internal governance subsystem composed of decision agents that collect data from their specific domains of control, process the data to determine if any actions are required, and if so, what, and then issue command signals to actuators to carry out those actions.

No system is sustainable without a well-functioning governance subsystem. At various places in the book we will be referring to, what for us, is the most important system on the planet, the human social system (HSS), which at present has global dynamics but no real global

³³ In Mobus & Kalton (2015), Chapter 10 – Emergence, section 10. 3.2.4, we describe the process by which simpler components interact with one another to form composites which must then survive a selective environment. Those configurations and any behaviors that result from them that do survive are said to have emerged. The fact of their survival shows that they are fit in that particular environment. In section 10.2.1.4 – Fit and Fitness, we had given the criteria for being fit in an environment.

governance subsystem in place to regulate the internal actions. We do not really control our population growth or resource depletion behaviors in order to be in balance with our environment – the rest of the planet. Moreover, most of our national governments are actually not really very functional from the systems perspective on governance. One of our greatest challenges in systems science will be to bring to the fore where our more common ideas of governance (and political process) deviate from systemic ideals and suggest ways in which these can be corrected for the sake of the HSS sustainability.

1.4.2 Systems Science as a Meta-Science

Though the application of systems science to engineering and development of human-built artifacts, including our own systems of governance, will have a huge benefit for humanity and the rest of the world, the sciences can benefit from its application as well.

Already most of the sciences have branches, some mainstream, that are called ‘systems <subject>’, where <subject> is a placeholder for name of the science. Systems biology is, perhaps the most prominent. Many of the original founders of systems science were primarily biologists (Miller, 1978; von Bertalanffy, 1968; and for a general overview, Capra & Luisi, 2014). However, people from diverse areas such as management theorist were very fast to take up the systems perspective in understanding management science and especially understanding management information systems in terms of information theory and cybernetics (Beer, 1966).

Most of the sciences that have adopted some aspects of systems science to their methodological approaches (i.e., systems modeling) have benefited from the insights gleaned from doing so. In systems ecology, for example, H.T. Odum (1994) used a systems modeling methodology to gain a deeper understanding of how energy flows through an ecosystem worked to shape and sustain that system.

However, there is much more than methods for modeling that could be gotten from applying rigorous systems science to any science. With the principles described above, along with others that derive from them as described in Mobus & Kalton (2015), scientists would know a priori that their objects of inquiry would be subject to considerations of network and hierarchical organization, internal and external communications, regulated energy and material flows, and so on. Basically, they can address their subjects more holistically than has been the general practice up until the present century. System theory should aid in better understanding theories in the sciences. For example, social scientists are already making great strides in understand social dynamics from a systems perspective, using network theory, auto-organization theory, game theory and many other aspects from systems science. Presently, they have developed their own methodological approaches (similar to the biologists), and have, in fact, contributed to a better understanding of some systems theory issues applied to human beings and societies. It stands to reason that if they work at connecting all of the principles of systems to their subjects they will gain new, more general insights into human social systems.

1.4.2.1 Understanding the Universe

The goal of the sciences (both natural and social) is to come to understand the way the world works. The ‘world’, as used here, means the Universe and us as well. This statement is not an argument in favor of scientism, the view that science is the ‘only’ way to gain knowledge. It is simply an observation of how the work of the sciences has proceeded over the last several centuries. One cannot argue against the successes thus far achieved (without denying some kind of objective reality). Our grasp of physical reality today is a simple fact, validated by our ability to produce artifacts, machines, medicines, media, and all aspects of culture.

So, without denying that there may be other forms of knowledge about realms of some reality that is not, strictly speaking, physical, we start with the presumption that insofar as physical reality is concerned, so far, the sciences have provided humanity with a working understanding of how things work.

Up until quite recently the work of science has proceeded along a path based on a mostly analytical methodology. The version of the scientific method taught in schools reflects the philosophical approach to gaining understanding called ‘methodological reductionism.’³⁴ This is, essentially, the idea of finding explanations for phenomena (or objects) in terms of component phenomena (or objects). Analysis is the process of decomposing (or deconstructing) something to find out what it is made of and trying to understand its workings based on the composition found. For example, living cells are composed of biochemical molecules, which are, in turn, composed of atoms (the mnemonic CHNOPS, carbon, hydrogen, nitrogen, oxygen, phosphorous, and sulfur captures the main elements), which, in turn, are composed of subatomic particles, etc. The behaviors of atoms are based on the behaviors of the subatomic particles (e.g. the formation of various kinds of bonds based on the properties of electrons in their orbitals around the nuclei).

But, as science has explicated the way the world works it has run into some interesting problems with its methods. It isn’t enough to explain how life is based on chemistry. Life has properties and behaviors that knowledge of chemistry alone cannot explain from below. For example, where does the motivation of living systems to survive and replicate come from? Biologists observe this living mandate but there is nothing in chemistry, even organic chemistry, which would necessarily predict that cells would strive to survive and reproduce.

The properties and behaviors of living systems are emergent from interactions between extremely complex organic chemistry subsystems. They have to be observed in action (in situ) to be appreciated. After that, deconstruction of the metabolic and reproductive processes can show

³⁴ Not to be confused with a philosophical posture, also called reductionism, in which it is asserted that all phenomena can ultimately be ‘explained’ by lower level phenomena. What systems science has lent to this notion is the concept of emergence, in which higher order phenomena are found that could not have been predicted just from the properties or behaviors of the constituents a priori. Methodological reductionism recognizes the need to describe the higher order phenomena first and then look for underlying phenomena that a posteriori can be seen to explain the higher order phenomena. There is an extensive literature on emergence but, of course, we recommend Mobus & Kalton (2015) for a concise overview.

1 how the biochemical processes produce these phenomena. There is no known way to go the other
2 way, from biochemical to phenomena.

3 The biological grasp of what biochemistry does (and means) is a clear example of a systems
4 approach to understanding³⁵. Methodological reductionism is a necessary step toward
5 understanding but only when predicated on a holistic model of the phenomena of interest. That
6 is, the system must be appreciated in its whole behavior before trying to grasp how the system
7 works from inside. We shall be attempting to apply this lesson from biology to the full range of
8 sciences. Systems science offers an approach to understanding how low level (organization)
9 phenomena translate, through emergent properties and behaviors, to more complex yet
10 understandable higher order phenomena.

11 Understanding, however, is not as straightforward as might be supposed. There are actually
12 two levels of what we call understanding. There is the kind in which we can make simple
13 predictions of what might happen in terms of a system's future behavior. And then there is the
14 kind where we can explain WHY a system might behave the way it does.

15 1.4.2.2 Shallow Understanding

16 What do we mean when we say we understand something? There are at least two senses
17 implied by the word 'understanding.' Both carry the idea that we can predict the future behavior
18 of a system or predict that instances of an observation of a system's state will be within
19 particular bounds. But such prediction can be based on a "shallow" understanding of the system.
20 It derives from many prior observations of the system's behavior under varying conditions
21 (environmental) along with a recording of the history that allows us to make predictions about
22 behavior under conditions not yet observed. We treat the system as a 'black box'³⁶ wherein we
23 know nothing about how the system transforms its inputs into output behaviors. We just know
24 that it does. Observational sciences, those that rely on observation of natural phenomena and use
25 statistical methods like linear regression analysis to capture some behavioral tendency, are often
26 stuck with this sort of understanding.

27 Often a shallow understanding of a system is all we can expect to get. For example, when
28 trying to understand the behavior of a particular animal species we can only watch and record the
29 conditions of the environment and the animals' responses to it. We have to collect large amounts
30 of data and analyze it using these statistical tools to see if a pattern emerges that can lead to
31 prediction. But being able to successfully predict future behavior based on past observed
32 behavior in observed environments does not guarantee that those predictions will hold when a
33 completely new kind of environment presents itself. The temporal window of observation may

³⁵ Which may help explain why the greatest and most comprehensive advances in understanding systems came from biologists!

³⁶ The term comes from the engineering world and is used to describe a machine, the internal mechanisms of which are unknown. All that can be discerned is its behavior. See the Wikipedia article:
https://en.wikipedia.org/wiki/Black_box

1 have been too short to accommodate all of the possible scenarios and hence fail to produce a
2 correct prediction under what might be rare conditions.

3 Experimental sciences are not limited to merely observing. They can conduct designed
4 condition experiments that extend the notion of a temporal window and rare conditions. For
5 example, a behavioral biologist might be interested in how a particular species of ant reacts to a
6 lower temperature than has commonly been observed in the wild. Setting up that experiment
7 would be relatively simple and yield data that would extend the inferences about behaviors'
8 correlations with conditions.

9 Even so, the observations of behavior remain in the realm of shallow understanding. What
10 would be nice to know is how that ant species adapts internally to low temperatures (if it can).
11 And to do that you need to do some dissection.

12 **1.4.2.3 Deep Understanding**

13 If you really want to understand something you have to find out *how* it works, how its
14 behavior under different conditions derives from those inner workings, and be able to predict its
15 reactions to various kinds of inputs on “first” principles, i.e. based on kinetics or internal
16 dynamics. When you can do that last part, you can claim to have a basic understanding of the
17 thing. Doing a good job on the first two, finding how it works and how it behaves brings you a
18 long way to the last – prediction. Being able to say how something works generally means
19 knowing something about its component parts and how they interact with one another, especially
20 the roles they play in transforming inputs to behavior and outputs. Observing and collecting data
21 regarding behavior over time and over a wide distribution of inputs, is still important so as to
22 confirm one’s predictions based on this deeper understanding. The more thorough the job one
23 does the deeper ones understanding goes.

24 But really deep understanding comes from continuing to “deconstruct” the internal
25 components themselves. This is the framework of systems analysis that we will be exploring
26 (forgive the pun) in depth in Chapter 5.

27 We must take a moment and explain the use of the word “deconstruct” in the previous
28 paragraph. To deconstruct something means to take it apart to evaluate its internal components. It
29 does not necessarily entail *separating components* from one another (as in dissection) and, in
30 fact, can include the notion of keeping track of the connections between components so as not to
31 disrupt the organization. Consider an analogy that might be useful. Suppose a biologist wants to
32 examine a single celled organism. She might first put the organism under a microscope low-
33 power lens to observe it from the outside. She might take pictures of the organism as it swims
34 about in its medium. She might observe its behavior as she introduces various compounds into
35 the medium to see how the organism reacts to them. She might take chemical samples of the
36 medium to see what sorts of molecules the organism is exuding. But at some point, when she has
37 a good idea of what the organism does, she decides to put it under a higher power lens that

1 allows her to see inside the organism without disrupting it. She sees a multitude of organelles,
2 tiny subsystems that carry on the internal work in the organism. She can catalog all of the various
3 kinds, get some accounting of their numbers, and perhaps see some connectivity between them.
4 Then she shifts to an even higher power lens to look at more details, perhaps now an electron
5 microscope has to be brought in. One by one she examines the structure and functions of the
6 organelles. She might note how mitochondria take in low weight carbohydrates and pump out
7 ATP molecules. Still not disrupting the cell, she can see how outputs from one kind of organelle
8 are inputs to other kinds.

9 This is the sense in which we use the word “deconstruct” and the process of
10 “deconstruction.” The objective is to not disrupt the workings at finer levels of resolution, but to
11 preserve the whole system’s integrity as much as possible in order to understand how the parts
12 activities contribute to the whole. Later we will be elucidating the process of structural/functional
13 deconstruction in systems analysis and show how its aim is explicitly to maintain functional
14 organization of the system being analyzed. This is different from many traditional reductionist
15 approaches (mentioned above) where the methodologies may leave a system disrupted because
16 of a belief that knowing what the parts are is all you need to know to explain the whole. We have
17 learned that this belief is in error most of the time.

18 Understanding the world and the things in it, like ourselves, our society, our complex
19 technologies, and the environment is the principal endeavor of humanity as it seeks to shape its
20 world in wise ways. Not knowing how things work is dangerous. If we act on ignorance instead
21 of understanding we risk unintended consequences. Humanity is facing that situation right now
22 in the form of global warming and climate change that will dramatically alter our environment in
23 ways that may involve existential threats. Acting with shallow understanding gets us into trouble.
24 It takes deep understanding to advance our situation keeping within the limitations imposed by
25 the natural world – the laws of physics and chemistry, for example.

26 Deep understanding has been the purpose of science. Science is a process, a self-correcting
27 process that works to increase our understanding of the world and everything in it. It operates
28 primarily by observing and measuring, by finding mathematical or formal descriptions of
29 phenomena, by dissecting phenomena into components, and by modeling phenomena so as to
30 make predictions.

31 However, science has been operating in a fractured, almost haphazard way, though it has
32 been evolving toward greater organization due to the way the results of science are accumulated
33 and organized. Individual scientists observe various phenomena and investigate their often small
34 piece of the puzzle. Science has focused on a reductionist approach to gaining understanding.
35 This is a historical phenomenon that resulted from starting from a base of ignorance of things,
36 and a limited ability for individual scientists to envision a larger or more holistic picture of how
37 their phenomenon of interest fit into that larger picture.

As the sciences have evolved (or matured), from ignorance to greater understanding, an interesting new phenomenon has emerged. More and more, the sciences are turning to system *thinking*, a system *perspective*, and a concern for interactions between numerous phenomena and subsystems. They are turning more and more to a systemic approach to gaining understanding and are recognizing that the real basis for deep understanding is not mere reductionist exposure of the components, but a concern for how those components interact with one another to produce the larger behavior of whole systems.

Systems science is about understanding the systemness of things in the world (as depicted in Figure 1.1). It is a science that explores the nature of being a system, of classifying kinds of systems, and developing the methodologies for applying principles of systems science to the other sciences and engineering as they become more systemic. This book is about the latter aspect.

1.5 What Goes Wrong

In this final section we examine some of the issues that arise from not following a principled approach to system understanding. That is, what kinds of problems do we experience when we attempt to design and build an artifact, or generate a policy, or understand a complex scientific problem when we are not using a whole systems approach to the work? Here we will briefly take a look at a few examples of areas where the work of systems analysis and design are not based on the principles of systems science but on systems intuitions and more casual systems thinking. Along the way we will point out the issues that arise and discuss how a failure to take a particular principle, or set of principles, into account can lead to less than desired results.

1.5.1 The Software Development Process

1.5.1.1 A Bit of History

Our first example comes from the Information Technology (IT) arena. Information systems, as used in organizations primarily for the assistance they provide in management decision making, were understood to be complex very early on. During the early 1970s large corporations, particularly banks, were beginning to adopt computers to automate routine account management functions. The use of computers, what were called ‘mainframe’ machines, spread rapidly as the tools for building large software systems were developed.

For example, the COBOL (COMmon Business Oriented Language) had been designed initially in the late 1950s and standardized in 1968³⁷. With that standardization and the construction of compilers by mainframe manufacturers, a cadre of specialists called “systems

³⁷ COBOL was an early English-like programming language, often attributed to the work of Grace Hopper. It was designed specifically to support the development of business information management computing support. See: Wikipedia <https://en.wikipedia.org/wiki/COBOL> and https://en.wikipedia.org/wiki/Grace_Hopper for more history.

analysts” arose to help translate the management needs of business workflows into computer programs that would automate those workflows. Early popular programs were developed for the organizations’ accounting needs, such as payroll, accounts receivable, and accounts payable. Over a relatively short period of time other business needs were automated, especially inventory management. The success of these early information systems can be attributed largely to the fact that the underlying workflows that needed managing had been in practice, literally, for centuries. The accounting practices in standard business were so well understood that the translation task was generally straightforward. Paper-based processes were replaced with computer-based ones more or less directly. Analysts did not have to actually deeply analyze the accounting procedures as if they were ‘new’ applications. The designs were simply assumed from the existing paper-based procedures. In that environment, the only problems that generally arose were the result of programmers making mistakes while coding, leading to logic errors (bugs) in the programs. The most insidious bugs were those that only showed up on rare occasions due to particular but uncommon inputs. They were often not detected in pre-deployment testing and only showed up during field operations. The software industry (both third-party and in-house developers) got used to maintaining their code, which actually meant fixing bugs when they surfaced. On the whole this was manageable. The costs were believed to be offset by the increased productivity gained using automation.

Once traditional accounting processes were automated the role of systems analysts came to be associated with helping accounting managers decide what reports (data summaries) they wanted to get from the now-computerized data files. The analysts were needed because they understood what could be done through the report generation languages and how to access the various files needed to process the data. Systems analysis became a process of local problem solving – one report at a time. The generation of a report only depended on the location (file) and disposition (age) of the data and not on the whole system. This practice may have been the origin of practices that persist to this day – to do analysis by asking users/stakeholders what they want from some particular ‘new’ system, rather than do a true systems analysis of the whole system as context for the development and design of processes to achieve the goals.

Problems started to emerge as the technology became more complex. Complexity also affected the nature of the business processes being automated. Distributed mini-computers were employed to manage different aspects of business workflows. For example, manufacturing companies sought means of monitoring and controlling the flow of materials from inventory through manufacturing to finished goods. Marketing and sales wanted to track customers’ orders and deliveries. These kinds of operations are non-standard across industries and even within industry types there are many variations and specializations of needs. Hence the nature of IT systems began to include heterogeneity of sub-processes. In addition to structural complexity increasing, the distribution of computing nodes while still needing cross-organizational cooperation led to the need to solve problems in concurrency, the coordination, synchronization, and communication of state information between processes.

1.5.1.2 IT Development Failures

Information Technology projects conducted by businesses and government agencies tend to be extremely complex, involving hundreds to thousands of “users,” managers (decision makers), and affecting numerous stakeholders such as customers or clients, and suppliers. They involve computing and communications equipment and the software to make them work. The main source of trouble seems to be in the software development. Software has unique system component properties that make its development subject to many sources of problems.

For the most part software development is conducted in planned projects by project managers whose job it is to integrate all of the components into a working subsystem. Those projects are managed with the intent of producing and delivering the software modules for the economic benefit of the organization and stakeholders. For now, we report a sobering fact that has been plaguing the software development industry ever since the level of complexity (above) rose beyond a straightforward payroll system. Most projects suffer some kind of failure that costs in wasted effort, lost revenues, and other economic consequences.

Projects don’t generally have a binary result – success or failure. However, we can categorize project results into those categories with shades of grey. Success or failure potentials can be measured along several dimensions. Reasonable metrics to use include project costs, delivery schedule, and final performance (compared with requirements). By these criteria most software development projects experience some degree of failure. According to a report published by the Standish Group from a 1995 survey of IT managers an average success rate (on-time, on-budget) was a paltry 16.2% with less than 50% of originally specified functionality delivered³⁸. According to this report, in 1995, approximately \$81 billion dollars were to have been spent by American companies and government agencies for projects that were likely to have been cancelled before completion. This amount is compared to approximately \$250 billion spent each year on software development. And this was 1995!

Have things improved since the end of the last century? Ten years later a report posted on the IEEE Spectrum site, “Why Software Fails: We waste billions of dollars each year on entirely preventable mistakes”, by Robert N. Charette (2005):

This year (2005), organizations and governments will spend an estimated \$1 trillion on IT hardware, software, and services worldwide. Of the IT projects that are initiated, *from 5 to 15 percent will be abandoned before or shortly after delivery as hopelessly inadequate*. Many others will arrive late and over budget or

³⁸ The Standish Group web site: <http://www.standishgroup.com/> Accessed: 10/26/2016. The group report: Chaos at <https://www.projectsmart.co.uk/white-papers/chaos-report.pdf> Accessed 10/26/2016. There have been dissenting voices to the results reported then (see this Dr. Dobbs report by Scott W. Ambler, The Non-Existent Software Crisis: Debunking the Chaos Report, February 04, 2014 <http://www.drdobbs.com/architecture-and-design/the-non-existent-software-crisis-debunki/240165910> Accessed: 10/26/2016)

1 require massive reworking. Few IT projects, in other words, truly succeed.³⁹
2 [emphasis added]

3 In the same article Charette gives the following list of “reasons” that projects fail:

- 4 • Unrealistic or unarticulated project goals
- 5 • Inaccurate estimates of needed resources
- 6 • Badly defined system requirements
- 7 • Poor reporting of the project's status
- 8 • Unmanaged risks
- 9 • Poor communication among customers, developers, and users
- 10 • Use of immature technology
- 11 • Inability to handle the project's complexity
- 12 • Sloppy development practices
- 13 • Poor project management
- 14 • Stakeholder politics
- 15 • Commercial pressures ^[footnote 29]

16 This list actually applies to more than just software development projects. In Chapter 4 we
17 will provide a sketch of the systems analysis process and use items from this list to demonstrate
18 how a full analysis based on systems principles would greatly reduce the negative impacts of
19 failures. For now, note that the first three items above all point to a simple fact – ignorance of
20 what the system would or should be – and not bothering to gain that understanding before
21 commencing the design. But it goes deeper than not understanding the IT system requirements.
22 Most information systems that are delivered but fail to produce adequate results do so because
23 the real system isn’t just the IT subsystem. It is the underlying work process that is being served
24 by the IT system. It is impossible to understand the requirements of an IT system without
25 understanding the system being served and all of its subsystems. This will be thoroughly
26 explored in Chapter 5.

27 And what about today (as of 2015)? The IEEE Spectrum has posted an interactive web site
28 that allows users to explore the costs of failures globally⁴⁰. Basically, it appears that the industry
29 hasn’t learned anything from these failures, perhaps a result of the multi-factor aspects of the
30 complexity of projects and their environments. But upon post-crash analysis (Charette, 2005)
31 most or all of the problems that caused the failure were, in some sense preventable.

32 It is the contention of this book that following a more rigorous systems approach than is
33 typically done would uncover most of the problems before a significant amount of money is
34 thrown away.

³⁹ See: <http://spectrum.ieee.org/computing/software/why-software-fails> Accessed: 10/26/2016.

⁴⁰ See: <http://spectrum.ieee.org/static/the-staggering-impact-of-it-systems-gone-wrong> Accessed 10/26/2016.

1 In truth, the main form of systems analysis that is practiced in all of the various forms of
2 project management rely on a weak questioning of the users, stakeholders, managers, etc. This is
3 called requirements gathering and even when it is backed by supposed quantitative measures it
4 suffers one major flaw. Usually and commonly the users, et al, *do not actually understand their*
5 *own requirements* nor do they have a language with which to articulate them if they did. In
6 Chapter 4 we provide a few examples of situations where users' claims for what was required
7 was later shown to be incorrect after the development work had already gotten underway. It is
8 interesting to note that the software development project management community has reacted to
9 these kinds of examples by designing methodologies that attempt to work around this problem.
10 So-called agile and iterative methods have evolved in which users are actually considered part of
11 the development team and the systems are developed in modules quickly allowing users to
12 actually see the results, and most importantly, change their minds at an earlier stage in
13 development. This approach has helped to some degree but in terms of dollars lost, these
14 methodologies have only shaved about ten percentage points off of the experiences of the "heavy
15 planning" approaches of the 1970s and 80s.

16 1.5.2 Systems Engineering Process

17 Systems engineering⁴¹ involves quite a lot more than just designing an information system
18 alone, however many of the approaches used in systems engineering are similar to software
19 engineering⁴². Today we design whole physical operations, machinery, labor, and management
20 subsystems together. Large scale products like supercolliders and jumbo jets involve every
21 conceivable engineering input to bring everything together in an integrated and fully functioning
22 whole. This means that not only do the engineers have to concern themselves with developing
23 software, they also have to develop every physical and 'mental' aspect of the system. They have
24 to coordinate the efforts of mechanical, electrical, materials, chemical, and sometimes many
25 more engineering experts. The scale of complexity in these efforts are many times greater than
26 an IT project alone.

27 One of the more famous examples of a massive system design failure was the baggage
28 handling system at the Denver airport (DIA). This subsystem of a megaproject was supposed to
29 speed up baggage handling and save labor costs. The system was supposed to serve all of the
30 airlines using DIA, which was itself a huge modern airport, designed for expansion. It involved
31 many mechanical sub-subsystems (e.g. the conveyor belts and their drive motors, switching
32 equipment, etc.) as well as the computer controls that were supposed to route the movements of
33 baggage from airline to customers or from service desks to the correct flights quickly and
34 efficiently.

⁴¹ See the Wikipedia article: https://en.wikipedia.org/wiki/Systems_engineering for more background.
Accessed 10/27/2016.

⁴² For the rest of this book we will consider all such engineering processes as systems engineering, i.e. software engineering is a subset of systems engineering.

Unfortunately, the system never worked⁴³. In several post-mortem analyses many of the problems given in the Charette list above were found to be operative. Megaprojects⁴⁴ are large complex, systems that require multidisciplinary-based engineering. Their purposes are to solve really large problems such as integrated transportation, energy production and distribution, and healthcare. They have become increasingly popular globally and they have proven to be extremely costly in terms of cost overruns and late completions (Flyvbjerg, et. al., 2003). They reflect the same sets of problems encountered in software projects but with massively greater risks and costs. As the global problems facing humanity grow and require mega-megaprojects to tackle solving them, the need to learn how to approach them is extreme. This is especially true given the decreasing resources that are available to the world (Meadows, et. al., 2004).

1.5.3 The Sciences

It would not be entirely correct to claim that science “goes wrong.” But it is correct to claim that science goes slow. The process of science has been guided by principles evolved from the earliest thoughts of empiricists such as Roger Bacon (circ. 1219/20 – circ. 1292)⁴⁵. The discipline of the scientific method and the process of doing repeated experiments (or making repeated observations), even when occasionally faltering, tends to cause the convergence of understanding over time. There is nothing particularly wrong with this process. Except that we might not have the luxury of time to let things work themselves out. Moreover, we’ve already argued that the complexities associated with phenomena of modern interest has reached a point where simple single disciplinary approaches cannot always make progress.

We assert that the methods described in this book are as appropriate for the scientific process as for the design process. Indeed, the systems analytic procedures, which preserve the holistic relations needed to reconstruct the system of interest in model form, is just starting from a higher-level view of the whole process. The sciences are already moving toward systems approaches and this is particularly the case for interdisciplinary investigations.

The systems approach as developed in this book adds a higher-level principled integrating framework for all of the sciences, natural as well a social. In Chapter 8 we will take an in-depth examination of a scientific approach to economics, typically thought of as a social science and therefore not subject to the same kinds of methodological disciplines as the physical sciences. We will show one approach that is capable of replicating more quantitative methods for economic questions because it follows the systems approach to the subject. We would like to put to rest the myth that social sciences are “soft” because their subject matter involves human

⁴³ See the Wikipedia article: https://en.wikipedia.org/wiki/Denver_International_Airport#Automated_baggage_system for a description. Accessed 10/27/2016.

⁴⁴ See the Wikipedia article: <https://en.wikipedia.org/wiki/Megaproject> for more background. Accessed 10/27/2016.

⁴⁵ See the Wikipedia article: https://en.wikipedia.org/wiki/Roger_Bacon for more background. Accessed 3/6/2017.

1 beings. The principles of systems science are used to demonstrate that as we go up the hierarchy
2 of complexity and levels of organization, the same rules apply even though they manifest in far
3 more complicated ways.

4 We believe and will argue that using the systems approach as an umbrella framework for all
5 of the sciences will make scientific investigations more efficient.

6 **1.6 What Could Go Right**

7 The main contention of this book is that all human activities aimed at gaining knowledge,
8 and particularly understanding, will benefit from apply the principles of systems science and the
9 methods described in this book. At very least the knowledge gained will be “pre-integrated” into
10 the larger body of knowledge of the world by virtue of tying the system to the sources and sinks
11 of its inputs and outputs, its environment. For example, we will demonstrate in Chapter 8 how
12 analyzing economic phenomena as a system can provide a stronger (and more scientific) linkage
13 with other subsystems of the human social system such as the education subsystem, which is
14 supposed to be a beneficiary of the former.

15 Similarly, we will have examples of how systems engineering, if pursued under the
16 framework of the principles of systems, will result in much higher quality products, services, and
17 policies for designed systems. This comes in the same form as for the sciences. The system of
18 interest is automatically and firmly tied to its environment. The principles of systems science
19 will ensure that the designed system will fulfill its purpose – it will be *fit* in its environment.

20 In the background of all of this is the idea that doing things right the first time will reduce
21 overall costs in the long run. Doing so will help make sure resources will be conserved and
22 available to other efforts in the future. It will reduce operating costs, in the case of designed
23 systems, and curating costs in the case of natural systems. Structuring knowledge for ease of
24 access and making sure that knowledge is complete will reduce search time (and costs) in the
25 future. Finally, being able to, at the push of a button, generate various models for visualization
26 and simulation provide ready access to many views of a system of interest and provide ways to
27 test hypotheses about the behavior of the system under conditions not necessarily observed in
28 nature or designed for originally.

29 **1.7 Proceeding with Principled Methods**

30 Throughout history humans have demonstrated time and again that once basic principles of
31 nature were learned and applied the quality of knowledge gained subsequently improved
32 substantially. This book will attempt to apply the principles discussed above, and the general
33 theory of systemness, to a methodological approach to furthering the knowledge we have of how
34 the world works. Such knowledge is becoming vital to our very existence as entities on this

- 1 planet. Our hope is that what is offered here will be seen as beneficial to the process of gaining
- 2 understanding and will be adopted, in some form, in time to make a difference.

3

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