Preface

Quick, think about a problem that vexes you. Too easy, right? The only difficulty you'd likely face is narrowing it down to *a* singular problem. Now think of another one. But this time, dig deep into your brain. Think of a problem that keeps you up at night, one that bothers you day in and day out, one that is seemingly intractable. Got one? Good, now think about what it is that characterizes this problem. What makes it hard? Why haven't you solved it yet?

Lyons (2004) offers the following barriers to solving what he calls *systemic problems*:

- Lack of incentives
- Limited resources
- Limited levers to change
- Limited power/authority
- Uncertain outcomes

We may summarize this list as saying that your problem is *complex*. But what, exactly, does that mean? What makes a problem complex? Is complexity a binary characteristic of a problem? That is, is a problem definitively complex or not? Does the complexity of a problem change throughout its development? These and more issues lead to perhaps the most fundamental introductory question for us, that is, how do we define complexity in a manner that is meaningful to us as practitioners and researchers.

Well, complexity is a loaded term. In fact, the notion of complexity is one that has been debated for decades in the scientific community and yet, no consensus on its definition has been reached (Gershenson, 2007; Lloyd, 2001; McShea, 1996; Mitchell, 2009). Precisely defining what is intended by the term complexity evokes former US Supreme Court Justice Potter Stewart's [1915–1985] famous description of obscenity, *I know it when I see it*; we know something is complex when we see it. Of course, from a scientific perspective, this is imprecise and problematic.

Literature abounds with measures proposed for evaluating complexity. We can measure the complexity of a system using a number of metrics such as Shannon's information entropy (Shannon & Weaver, 1949), algorithmic information content (Chaitin, 1966; Kolmogorov, 1965; Solomonoff, 1964), effective complexity (Gell-Mann, 1995), logical depth (Bennett, 1986), thermodynamic depth (Lloyd & Pagels, 1988), statistical complexity (Crutchfield & Young, 1989), hierarchy (Boulding, 1956; Simon, 1962), a set of predefined characteristics (Cilliers, 1998; Funke, 1991, pp. 186–187), and a number of other measures (Lloyd, 2001). Criticisms of these measures range from a lack of intuitive results when using some measures (information entropy, statistical complexity, and algorithmic information content) to the lack of a practical means for consistently utilizing other measures (logical depth, effective complexity, and thermodynamic depth). Mitchell (2009) discusses the drawbacks of many of these measures and suggests that none have obtained universal appeal as a practical and intuitive means of measuring the complexity of a system. McShea (1996) agrees, stating, "…no broad definition has been offered that is both operational, in the sense that it indicates unambiguously how to measure complexity in real systems, and universal, in the sense that it can be applied to all systems" (p. 479). In the absence of a universal measure of complexity, we will investigate two perspectives for defining complexity, namely characteristic complexity and hierarchical complexity, in an effort to provide some structure to the concept.

Characteristic Complexity

We may conceive of complexity as being measured by the extent to which a situation or problem exhibits a number of predefined characteristics. One such set of characteristics was posed by noted psychologist Joachim Funke (1991, pp. 186–187) as characterizing complex problem-solving situations:

- *Intransparency*: Intransparency refers to the lack of availability of information in our problem. An intransparent problem represents a situation in which all variables cannot be directly observed. In this case, we may have to infer information about the underlying state of the system, or too many variables exist, leading to our selection of only a handful for observation and analysis.
- *Polytely*: From the Greek words *poly* and *telos* meaning *many goals*. This set of goals can be thought in many forms. We may have many individuals associated with our problem, and each harbors their own needs and wants. These interests are likely not to be directly aligned; thus, they compete for our attention, requiring trade-offs. Similarly, objectives within our problem are not typically straightforward. Complex problems involve multiple, conflicting objectives. Finally, our problem will likely require competition for resources. We do not have unlimited resources; thus, we are limited in our ability to address our problem in the most straightforward and effective manner.

- *Complexity*: Here, Funke is referring to the number of variables, the connectivity between these variables, and the nature of their relationship (i.e., linear vs. nonlinear). Funke (1991) summarizes complexity as:

  > A complex problem-solving situation is not only characterized by a large number of variables that have to be considered, but also by their complex connectivity pattern, by the possibilities to control the system, and by the dynamic aspects of the system. The growing complexity of situational demands may conflict with the limited capacity of the problem solver. (pp. 186–187)

- *Variable connectivity*: A change in one variable is likely to affect the status of many other variables. Given this high connectivity, consequences are difficult to predict. That is, there is substantial unpredictability in the behavior of the problem. Even the most tried-and-true of modeling techniques fail to capture the behavior of modern problems—events such as Hurricanes Katrina or Sandy, the housing market crash, and other so-called *Black Swans* (Talib, 2007). These unpredictable phenomena go beyond the bounds of our uncertainty analysis techniques and require us to consider the robustness of our institutions, organizations, and supporting systems. Considering these phenomena in concert with shrinking resources, we have a quandary. More resources are required to plan for unpredictability, yet we lack sufficient resources to address these concerns completely. Thus, we must make compromises to account for this inherent contradiction.
- *Dynamic developments*: There is often considerable time pressure to address problems before they worsen. Positive changes also occur, but these changes could lead to further unpredictability. This is complicated by humans' bias for action. Most people are uncomfortable with situations that are unresolved. We want an answer and we want it now. One must simply look at the increase in information availability over the last decade to understand how the world has transformed into one demanding instant gratification. No longer are we content to pull an encyclopedia off our book shelf (that is, if we even own an encyclopedia anymore) and look up the answer to a question. Instead, we pull out our smart phone and *Google it*, expecting an instant answer, and grumbling when our Internet connection hits a snag. This behavior is problematic when the problems of substantial complexity are considered. Choosing to act, to get an answer *right now*, rather than obtaining additional information, may lead to an inferior choice based on insufficient information. We must carefully weigh the desire to obtain more information with our potential for loss and what may have been. To put it another way, we must choose between *getting it right* and *getting it right now*.
- *Time-delayed effects*: Effects often occur with a time delay. This requires patience on the part of the individual concerned with the problem. This is in direct contrast to the need for near-term action discussed in the previous element.

To this list, we add two characteristics:

- *Significant uncertainty*: Complex problems have substantial uncertainty. That is, there are unknown elements which plague our problem. Some are so-called *known unknowns* such as the fact that market demand for a new product is unknown. These uncertainties come from the variables that are known to exist in a problem (but that have some level of random behavior associated with them that can be expressed by probability distributions). These types of uncertainties are present in any real-world problem due to the inherent variability of the natural world. So we use probabilistic information to reason about and predict these phenomena. More difficult to deal with are *unknown unknowns* such as the fact that we do not know what our competitors will do. This type of uncertainty comes from lack of knowledge of the larger system of problems (which we will later classify as a mess) of which our problem is a part. Will we be instantly outclassed by our competitors the day our new product is introduced to the market (or worse, before we even release our product)? To estimate these uncertainties, we typically turn to experts for their insight. Both sources of uncertainty, known and unknown unknowns, complicate our problem landscape but cannot be ignored.
- *Humans-in-the-loop*: Designing a mechanical system given a set of specifications may be straightforward, but designing the same system while incorporating human factors, including elements such as ergonomics, fatigue, and operator error prevention, is substantially more complex. Once we insert humans into our problem system, all bets are off, so to speak. In many ways, humans are the ultimate trump card. They represent the one factor that seemingly ignores all the hard work, all the calculations, all the effort, that has gone into the development of a solution to our problem. They exploit the one weakness or vulnerability in our problem system that no amount of simulations, trial runs, mock-ups, or counter-factuals could have accounted for. They are intransparent, uncertain, competitive, unpredictable, and have a bias for action, all factors that we've indicated make a problem hard. To boot, they are not mechanistic; they have feelings and emotions, and difficult problems are often especially emotional issues. Think about some of the most difficult problems facing our current society, e.g., health care or higher education; they are highly emotional topics likely to elicit an emotionally charged response from even the most level-headed of individuals. Thus, even when we think we have it all figured out, humans enter the equation and blow it all apart.

Hierarchical Complexity

Conversely, it may be advantageous for us to think of complexity as existing in a hierarchical fashion. Jackson (2009) summarizes the work of Boulding (1956) in creating a nine-level hierarchy for real-world complexity, as shown in Table 1 and in keeping with the *principle of hierarchy* (Pattee, 1973).

Table 1 A summary of Boulding (1956) hierarchy of complexity (Jackson, 2009, p. S25)

Level	Description	Example
1	Structures and frameworks which exhibit static behavior and are studied by verbal or pictorial description in any discipline	Crystal structures
2	Clockworks which exhibit predetermined motion and are studied by classical natural science	The solar system
3	Control mechanisms which exhibit closed-loop control and are studied by cybernetics	A thermostat
4	Open systems which exhibit structural self-maintenance and are studied by theories of metabolism	A biological cell
5	Lower organisms which have functional parts exhibit blue-printed growth and reproduction, and are studied by botany	A plant
6	Animals which have a brain to guide behavior are capable of learning, and are studied by zoology	An elephant
7	People who possess self-consciousness know that they know, employ symbolic language, and are studied by biology and psychology	Any human being
8	Sociocultural systems which are typified by the existence of roles, communications and the transmission of values, and are studied by history, sociology, anthropology, and behavioral science	A nation
9	Transcendental systems, the home of 'inescapable unknowables', and which no scientific discipline can capture	God

Each of these levels is of increasing complexity, and each contains emergent properties not found in the levels below. Thus, in seeking to understand a given level, we must also understand those levels beneath it, invoking the *principle of recursion* (Beer, 1979). Boulding (1956) comments on the maturity of our knowledge about the levels in his hierarchy:

> One advantage of exhibiting a hierarchy of systems in this way is that it gives us some idea of the present gaps in both theoretical and empirical knowledge. Adequate theoretical models extend up to about the fourth level, and not much beyond. Empirical knowledge is deficient at practically all levels. Thus, at the level of the static structure, fairly adequate descriptive models are available for geography, chemistry, geology, anatomy, and descriptive social science. Even at this simplest level, however, the problem of the adequate description of complex structures is still far from solved. (p. 205)

Despite our relative naïveté about the higher levels of the hierarchy, Boulding (1956) notes that all hope is not lost:

> Nevertheless as we move towards the human and societal level a curious thing happens: the fact that we have, as it were, an inside track, and that we ourselves are the systems which we are studying, enables us to utilize systems which we do not really understand. (pp. 206-207)

Thus, even though we may not *understand* systems at the higher levels of this hierarchy in the theoretical sense, we can work with, utilize, and make sense of them. This is absolutely necessary as we attempt to determine the appropriate opportunity to intervene in a problem system.

So, what is one to do? Well, we could avoid all problems exhibiting one or all of the characteristics of complexity, existing within Boulding's hierarchy, or fundamentally identified as complex by us as researchers and practitioners. This leaves a very small, uninteresting subset of the world to deal with. Alternatively, we suggest that all hope is not lost. We simply need a new way to reason about these problems that goes beyond the traditional methods we employ. Full disclosure—the authors of this book are engineers by education. But we've worked in industry and the military for many years and we've come to understand that no single discipline can solve truly complex problems. Problems of real interest, those vexing ones that keep you up at night, require a discipline-agnostic approach. They require us to get out of our comfort zone a little bit, to reach across the aisle and embrace those fundamental concepts of other disciplines that may be advantageous to our effort. Simply, they require us to think *systemically* about our problem.

Fundamentally, we need a novel way to *address* these problems, and more specifically, to do so *systemically*, hence the title of this book. It is the hope of the authors that, after reading this book, readers will gain an appreciation for a novel way of thinking and reasoning about complex problems that encourages increased understanding and deliberate intervention. We set out to provide this in a manner that is not predicated on the reader being either an engineer or a scientist. Indeed, most of the complex problems vexing us are not engineering or scientific problems, at least in the strictest sense. Complex problems such as climate change, world hunger, poverty, and global conflict know no disciplinary boundaries. So, you'll see us draw from engineering and science to be sure, but we'll also draw from psychology, mathematics, sociology, management, and many other fields in an effort to develop a robust approach to thinking about and addressing problems. To support this approach, this book is divided into four major sections: (1) A Frame of Reference for Systemic Decision Making; (2) Thinking Systemically; (3) Acting Systemically; and (4) Observing Systemically.

This book is intended for use by practitioners tasked with addressing complex problems or individuals enrolled in a graduate or advanced undergraduate class. Given its discipline-agnostic nature, it is just as appropriate for use in a business, sociology, or psychology course as it is in an engineering or scientific course. Regarding its instruction, the chapters should be taught in order. Part I provides the proper theoretical foundation necessary for Parts II–III. Part II provides a multi-methodology for thinking systemically about complex problems and problem systems. Part III provides an approach for acting on the complex problems and problem systems investigated in Part II. Finally, Part IV discusses observation of actions undertaken in Part III, and it provides a comprehensive case study demonstrating the material discussed throughout the text.

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http://www.springer.com/978-3-319-54671-1

Systemic Decision Making
Fundamentals for Addressing Problems and Messes
Hester, P.T.; Adams, K.
2017, XXVIII, 414 p. 162 illus., 67 illus. in color.,
Hardcover
ISBN: 978-3-319-54671-1