Chapter 11
The *When* of Systemic Thinking

Abstract The *when* question of systemic thinking attempts to determine the appropriate time for interacting with our mess in an effort to increase our understanding about it. Recalling the TAO of systemic thinking, we must think before we act on (and observe) our mess. The understanding gained from our thinking informs when (and if) we decide to intervene in our mess. In order to discern the appropriate time for action, we explore two criteria of our messes, its *maturity* and its *stability*. These two criteria will first be explored by investigating life cycles and their relevance to the maturity of our mess. We will then explore the phenomena of evolution, as it pertains to both biological systems and to purposeful systems. Then, we will discuss entropy as it relates to evolution. Finally, we develop a framework to address the *when* as it applies to any efforts at intervention in our mess.

11.1 Life Cycles and Maturity

There are many similarities between biological systems and purposeful systems, but perhaps none is more fundamental than the basic life cycle each follows. Although there are more complex models for both in the biological and systems literature, we can summarize biological systems as comprising a "birth-growth-aging and death life cycle" (Sage & Armstrong, 2000, p. 7). Blanchard (2004) discusses a purposeful system's life cycle, saying it

> …includes the entire spectrum of activity for a given system, commencing with the identification of need and extending through system design and development, production and/or construction, operational use and sustaining maintenance and support, and system retirement and material disposal. (p. 13)

Succinctly, and in terms analogous to the phases associated with a biological life cycle, we may describe purposeful man-made systems as having a life cycle consisting of a definition (birth), development (growth), use (aging), and retirement (death). A depiction juxtaposing both life cycles is shown in Fig. 11.1.

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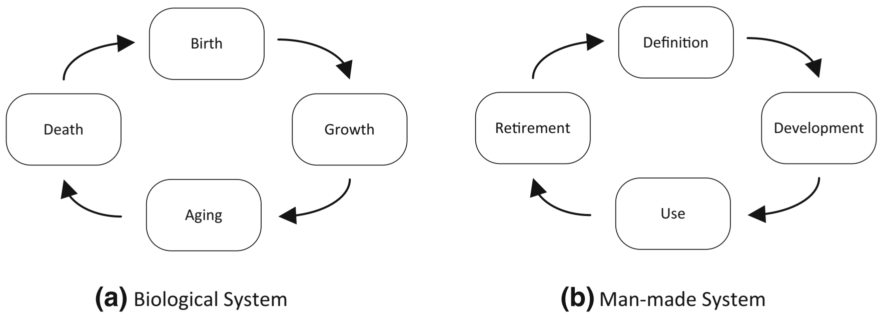

Fig. 11.1 Depiction of biological (**a**) and human-made system (**b**) life cycles

A short description of each stage as it pertains to purposeful man-made systems is as follows:

- *Definition*: Our system is *born* here. We begin to conceptualize it here by identifying a need that is to be satisfied by our system and determining the constraints on our system. As it concerns a mess, definition is an artificial construct. We define the context and environment of our system (see Chap. 8 for further guidance). We define the elements that comprise the mess as a construct of convenience; they likely have no real abstraction at the level we choose to analyze them. A perfect example is the education system in the USA. Our level of abstraction is subjective and purposeful; whether we wish to explore the national education system or the education afforded to the children in our home influences the lens through which we view the problem.
- *Development*: Our system begins to take shape. It matures and *grows* through iterative development and evolution. It may require resources to take a form that is either useful or recognizable to us.
- *Use*: Our system is in use. It requires maintenance and effort to sustain its performance at a level that is acceptable to its users. At this point, consideration and maintenance of our system's entropy (discussed at length in Sect. 11.4) become paramount to its continued viability.
- *Retirement*: Our system has fulfilled its intended purpose (and thus, it may be retired from service) or surpassed its expected life (and thus, it *dies* organically). In the context of a mess, this element is problematic as not all components will have the same timescale or life expectancy. Thus, we may need to invest resources into our mess in an effort to artificially extend its useful life.

The two cycles in Fig. 11.1 show significant similarity between the basic life cycles of biological and purposeful man-made systems. However, when we think about *messes*, which occur as a result of system operation and human involvement and are not purposefully *designed*, the conceptualization of a life cycle becomes a little less clear and orderly. Most notably, the *birth* and *death* of a mess are nebulous constructs. When does a traffic problem in a locality become a mess? When a second mode of transportation (i.e., public transportation) becomes available?

When it has to cross traditional jurisdictional boundaries (i.e., city, county, state, or country)? There are certainly several explanations for the birth of said mess that may be reasonable, and yet, none may be of any value. A more fundamental question may be whether or not the specific birth or death of our mess is a construct that is of any value to its observers. How it came into being (be it by our own purposive behavior or otherwise) and how it will cease to exist (be it by forced retirement, simply run out its expected life, or evolve into an entirely different mess of an unrecognizable nature) is likely of little value. More importantly, it is of interest to us to understand the *life* of our mess, and thus, we should primarily focus on the development and use of it, or to use biological terms, its growth, and aging. In concerning ourselves with its birth and death, we are likely to get mired in trivialities that are of no value. We must undertake a holistic consideration of the life of our mess. Blanchard (2004) agrees, noting

> The past is replete with examples in which major decisions have been made in the early stages of system acquisition based on the "short term" only. In other words, in the design and development of a new system, the consideration for production/construction and/or maintenance and support of that system was inadequate. These activities were considered later, and, in many instances, the consequences of this "after-the-fact" approach were costly. (pp. 14–15)

Noted systems engineer Derek Hitchins offers a unique, but complementary perspective which may help us. His principle of cyclic progression offers a lens to view our system's development through

> Interconnected systems driven by an external energy source will tend to a cyclic progression in which system variety is generated, dominance emerges, suppresses the variety, the dominant mode decays or collapses, and survivors emerge to regenerate variety. (Hitchins, 1993, p. 633)

This principle can be depicted graphically and annotated with the phases of the biological cycle discussed earlier as shown in Fig. 11.2. We can see the cyclic

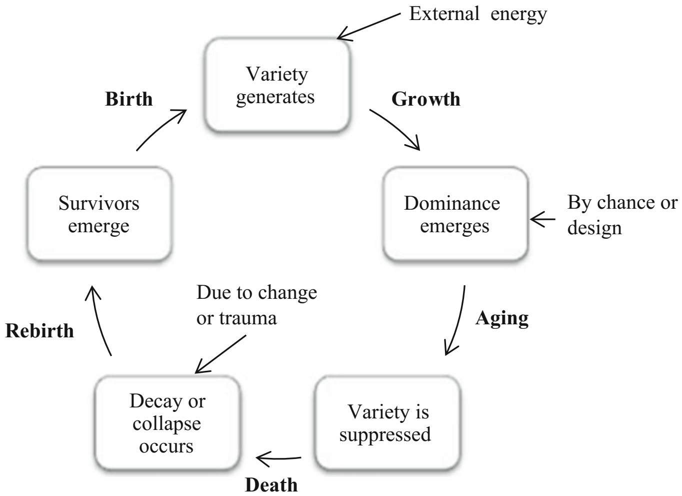

Fig. 11.2 Illustration of cyclic progression (adapted from Fig. 2.9 in Hitchins, 2007, p. 58)

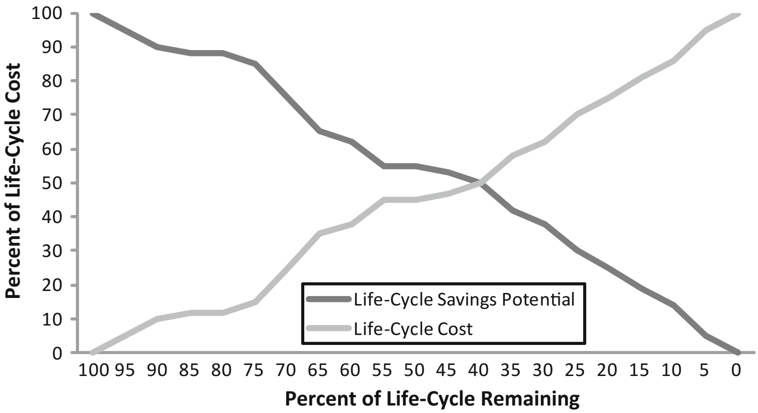

Fig. 11.3 Closed system life-cycle cost and benefit

nature of the life cycle as it is juxtaposed with Hitchins' illustration of cyclic progression.

The question then becomes, at what point in the life of our mess should we intervene? We can look to Fig. 11.3 to give us a clue. All closed systems have a finite life. Without intervention from external sources, our system will cease to exist (more on this and its related element of entropy are found later in this chapter). Thus, as the life of our system progresses, the cumulative costs associated with it increase and the potential for savings decrease. While the exact shapes of the curves shown in Fig. 11.3 vary depending on the circumstances, we know that the total cost is monotonically increasing (i.e., it never goes down), and the savings potential is monotonically decreasing (i.e., it never increases).

Thus, for any given system, every day that passes has the potential to incur more cost for us and present less opportunity for savings. So, should we just invest as early as possible? The answer is not so clear.

To answer this question, we can adapt the notion of a basic cost–benefit analysis (CBA). Traditionally in CBA, alternatives are designed for a system and we trade off their respective benefits (typically in terms of dollars) with their costs (also typically in dollars) as a ratio expressed in Eq. 11.1.

$$C/B = \frac{\text{Cost}}{\text{Benefit}} \tag{11.1}$$

The alternative with the lowest *C/B* is chosen as the preferred option to pursue. However, with a mess being so inherently unpredictable, it may not be advantageous for us to use cost and benefit in this sense. More importantly, we may consider the trade-off between cost and benefit as a litmus test of feasibility for considering whether or not to intervene in our mess (and thus, to commit resources). For such an analysis, we can invert Eq. 11.1 and consider the following relationship in Eq. 11.2.

$$\max(B/C) \geq 1 \tag{11.2}$$

Utilizing this inequality, we try to conceptualize if *any* option exists for intervention in our system that provides a larger benefit than its associated cost. This is of course a simplifying assumption in that it typically equates cost in dollars to benefit in dollars, but we can abstract the discussion to any relevant measure of merit.

Let us take a biological example. It would be difficult for a doctor to endorse an urgent heart transplant for a 95-year-old patient regardless of the circumstances (i.e., even if death is certain without the operation). The benefit of the operation may be conceptualized in a number of ways. For instance,

- Five years of additional life or alleviated pain for the patient can be compared to the cost associated with it, or
- The actual cost of the operation, the expected survival rate of the patient, or the risk of not providing the donor heart to a more viable (and arguably more deserving) patient.

It seems fairly straightforward that the inequality represented by Eq. 11.2 is not met. Complicating this scenario is its likely status as a mess. Maybe the patient would pay cash for the operation alleviating insurance concerns. Alternatively, perhaps there is a clearly more deserving patient (although it may seem abhorrent to some, merit-based rankings of individuals seeking a donor organ can be generated). These and other concerns make this quite a difficult scenario to understand. If we determine that the *B/C* ratio is not sufficient for this alternative, we can conceive of other options. One such alternative is to utilize hospice care for the patient in an effort to allow him to die with dignity. In this case, the cost is minimal (at least from the medical expenditure perspective, the *cost* to the world of losing the individual is another debate entirely, and one we would not dare explore) and the benefit is arguably justified by the cost. Thus, we have found a proposed solution that satisfies Eq. 11.2. In this way, we have satisfied the *maturity* concern associated with the when of systemic thinking. It is in this way that we should think of maturity.

If we take the ratio of the benefit and cost curves in Fig. 11.3 and plot them against the inequality of Eq. 11.2, we can generate the curves shown in Fig. 11.4. This graphic demonstrates that early on in our system development, there is a high potential for a high benefit to be realized from intervening in our system, given the significant expected life left in our system. Additionally, early in the development, it is cheap to change our system. At some point, when the curves cross, it is no longer advantageous to intervene in our system.

Figure 11.4 must be taken with two caveats as they pertain to a mess:

1. Messes exist in open systems. Open systems interact with their environment. As a result, they are unstable such that Fig. 11.4 can be recalibrated by interjecting resources into the mess. Thus, the *B/C* curve (and its underlying components of cost and benefit) can be improved or worsened by expending resources in the form of additional mechanisms (the focus of Chap. 10) on the mess. In doing so,

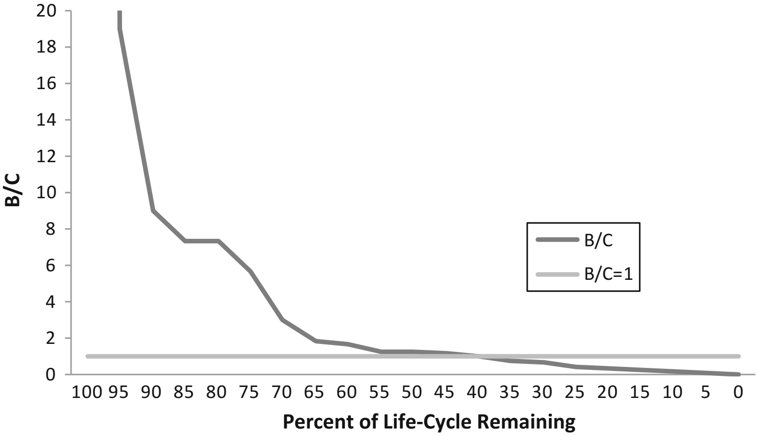

Fig. 11.4 *B/C* as a function of time

we have transitioned our mess, perhaps to a form that is unrecognizable to us (and hopefully to an improved state). Such potential transitions are illustrated in Fig. 11.5.

2. Figure 11.4 illustrates a system, not a mess. Messes are unpredictable. They are likely not to possess a clear crossover point. Thus, our understanding of the mess is likely to coincide with a range of options, such as those denoted by the improved and worsened curves in Fig. 11.5. This is largely due to the unpredictability of the system and due to the first caveat, i.e., our ability to make adjustments based on our limited understanding.

Thus, the guidance provided in this section is to be taken as a heuristic. The key takeaway of the maturity discussion is for us to consider the relative cost (monetary

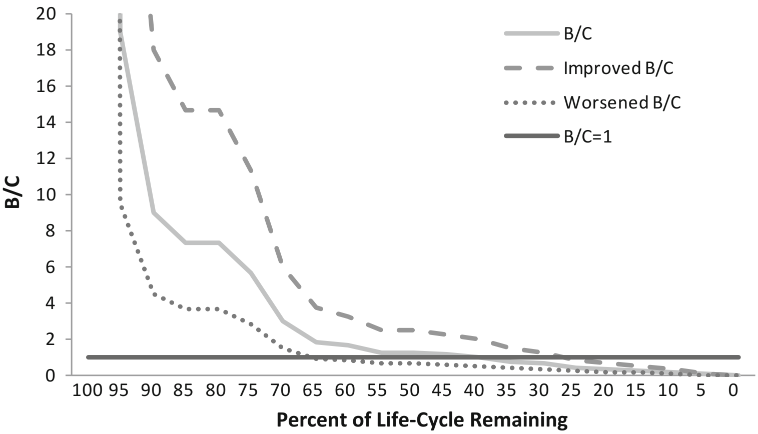

Fig. 11.5 Moving the *B/C* curve

or otherwise) and expected benefits resulting from increasing our understanding, especially if this increased understanding requires the expenditure of resources, before investing our time, money, and efforts. We must aim for the region above the *break-even* point for our mess (when $B = C$), but this is not the only concern. Given the unpredictable nature of our mess, we must also consider its evolution. Sage and Armstrong (2000) illustrate the linkage between life-cycle and evolution concerns: "This life-cycle perspective should also be associated with a long-term view toward planning for system evolution, research to bring about any new and emerging technologies needed for this evolution, and a number of activities associated with actual system evolution…" (p. 7). Indeed, the *stability* of our system, a measure equally as important as its *maturity*, must be considered by exploring its evolution and development.

11.2 Evolution

The development and evolution of our mess are continual. Understanding the mechanism of evolution and determining an appropriate time to intervene in our mess are a significant endeavor and yet one we are tasked with. First, we can explore the notion of evolution within biological, or living, systems. Many definitions for evolution exist. Several definitions taken from the biological complexity domain include

- Biological evolution is the process of gradual (and sometimes rapid) change in biological forms over the history of life (Mitchell, 2009, p. 72).
- Evolution here is simply robustness to (possibly large) changes on long timescales (Csete & Doyle, 2002, p. 1666).
- Evolution is the historical process that leads to the formation and change of biological systems (Johnson & Lam, 2010, p. 880).
- The word evolution comes from the Latin evolvere, "to unfold or unroll"–to reveal or manifest hidden potentialities. Today "evolution" has come to mean, simply, "change." (Futuyma, 2005, p. 3)

Each of the above definitions connotes change; however, only one, Csete and Doyle's, addresses the purposeful notion of change (they support that evolution exists to maintain system functionality despite uncertainty). As systemic thinkers, we support the notion of purposeful change in systems and we believe the following discussion will bear out a historical belief in this notion as well. Thus, for our purposes, we define evolution succinctly as *purposeful change in system structure or behavior*.

Jean-Baptiste Lamarck [1744–1829] developed arguably the most famous pre-Darwin theory of evolution, the idea that living organisms can pass characteristics they acquired throughout their lifetime on to their offspring. These acquired characteristics, or adaptations, were "changes for the better, or at least, for the more complex" (Mitchell, 2009, p. 73).

As Charles Darwin [1809–1882] and others rose to prominence, it was clear that the notion of acquired characteristics in biological systems was false. Darwin's voyages to the Galapagos Islands aboard the H.M.S. *Beagle* survey ship led to his empirical observations about the gradual development and adaptation of finches. His observations led to his belief in the idea of *gradualism*, the notion that small factors, extended over significant time horizons, could have long-reaching effects, and his publication of *The Origin of Species* (Darwin, 1859). Two major premises arose from this work, as summarized by (Futuyma, 2005):

- The first is Darwin's theory of **descent with modification**. It holds that all species, living and extinct, have descended, without interruption, from one or a few original forms of life….Darwin's conception of the course of evolution is profoundly different from Lamarck's, in which the concept of common ancestry plays almost no role.
- The second theme of The Origin of Species is Darwin's theory of the causal agents of evolutionary change…This theory is a VARIATIONAL THEORY of change, differing profoundly from Lamarck's TRANSFORMATIONAL THEORY, in which individual organisms change. (p. 7)

Mitchell (2009) adds one additional point of note regarding Darwin's beliefs:

- Evolutionary change is constant and gradual via the accumulation of small, favorable variations. (p. 79)

This theory was in sharp contrast, at least in the eyes of the early adherents of both, to Gregor Mendel's [1822–1884] *mutation theory*. Mutation theory stated that variation in organisms was due to mutations in offspring which drive evolution, with natural selection unnecessary to account for origin of species. Mendel's perspective evolved into the Evolutionary Synthesis or Modern Synthesis movement, which provided its own set of principles of evolution. Describing the development of its underlying theory, Futuyma (2005) notes

> Ronald A. Fisher and John B.S. Haldane in England and Sewall Wright in the United States developed a mathematical theory of population genetics, which showed that mutation and natural selection together cause adaptive evolution: mutation is not an alternative to natural selection, but is rather its raw material. (p. 9)

The idea of gradualism was questioned in the 1960s and 1970s, when paleontologists Stephen Jay Gould and Niles Eldridge began to challenge it as "very rare and too slow, in any case, to produce the major events of evolution" (Gould & Eldredge, 1977, p. 115). Instead, they proposed a theory of *punctuated equilibrium* (Eldredge & Gould, 1972) which instead hypothesized that "Most evolutionary change, we argued, is concentrated in rapid (often geologically instantaneous) events of speciation in small, peripherally isolated populations (the theory of allopatric speciation)" (Gould & Eldredge, 1977, pp. 116–117).

Despite this challenge, evolutionary synthesis remains crucial to our understanding of evolution today. "The principal claims of the evolutionary synthesis are the foundations of modern evolutionary biology…most evolutionary biologists today accept them as fundamentally valid" (Futuyma, 2005, pp. 9–10). While this consensus persists, many questions remain concerning the complexities of modern evolution. The presence of holistic connections in living systems complicates our understanding of biological organisms: “The complexity of living systems is largely due to networks of genes rather than the sum of independent effects of individual genes” (Mitchell, 2009, p. 275).

At this point, then, most of science believed that evolution alone, in one form or another, was responsible for the complexity inherent in biological systems. This perspective was in sharp contrast to that of theoretical biologist Stuart Kauffman; in studying complex biological systems, Kauffman has developed remarkable theories about evolution and complexity. Arguably, his most fundamental point is that biological complexity does not necessarily arise from a process of natural selection.

> Most biologists, heritors of the Darwinian tradition, suppose that the order of ontogeny is due to the grinding away of a molecular Rube Goldberg machine, slapped together piece by piece by evolution. I present a countering thesis: most of the beautiful order seen in ontogeny is spontaneous, a natural expression of the stunning self-organization that abounds in very complex regulatory networks. We appear to have been profoundly wrong. Order, vast and generative, arises naturally…much of the order in organisms may not be the result of selection at all, but of the spontaneous order of self-organized systems….If this idea is true, then we must rethink evolutionary theory, for the sources of order in the biosphere will now include both selection and self-organization. (Kauffman, 1993, p. 25)

Further, Kauffman’s *fourth law* introduced the notion that “life has an innate tendency to become more complex, which is independent of any tendency of natural selection” (Mitchell, 2009, p. 286). Kauffman’s book *The Origins of Order* (1993) talks at length about this concept.

Astrophysicist Erich Jantsch [1929–1980] contrasted internal and external self-organizing systems as those that change their internal organization and those that adapt their way of interacting with their environment, respectively. Jantsch (1972) discussed three types of internal self-organizing behavior useful to our study:

- mechanistic systems do not change their internal organization;
- adaptive systems adapt to changes in the environment through changes in their internal structure in accordance with preprogrammed information (engineering or genetic templates); and
- inventive (or human action) systems change their structure through internal generation of information (invention) in accordance with their intentions to change the environment (p. 476)

The systems we are concerned with reside in the adaptive or inventive classification. For our purposes, we are concerned with order and stability and what we may learn of purposeful systems by studying biological systems. If we can summarize, we may conceive of two major streams of evolutionary thought (1) those who believe natural selection is primary, be it via gradual means (e.g., Darwin) or punctuated means (e.g., Gould and Eldredge); and (2) those that believe that self-adaptation and self-organization have arisen via emergent behavior of biological systems (e.g., Kauffman). We may describe evolution by natural selection as being “conceived using data at the macroscopic level” (Johnson & Lam, 2010, p. 879) and thus as a meta-theory of the development of systems, whereas we may think of self-organization as “essentially present, but..not well controlled” (Johnson & Lam, 2010, p. 882) and thus an emergent, inherent property of both the system and its circumstances. It is our belief that these two perspectives may be complementary given their presence on differing levels of logical abstraction, and, in fact, both perspectives have implications for how we may seek to understand problems and messes. If we accept the parallelism of biological and purposeful system life cycles, then perhaps, it is not much of a stretch to understand the increasing complexity of both biological and purposeful systems. What drives this increasing complexity? Is it evolution *or* self-organization? We contend that a system that is to maintain its viability (Beer, 1979) must be allowed to evolve *and* self-organize. How to ascertain if our mess has evolved or is evolving; what about self-organizing? More fundamentally perhaps is, does it even matter? The answer, if we are to effect change, is yes. The answer in how to identify the opportunity for this change lies in the concept of entropy, to which we now turn.

11.3 Entropy

How do patterns emerge in systems and in nature? As if appearing to occur by some magical *slight of hand*, structure and patterns emerge in systems without external interference (i.e., they self-organize). This behavior is seemingly illogical, but some investigation will clarify how independent elements arrange themselves in an ordered and purposeful pattern. Understanding this phenomena and its role in systemic thinking requires that we first understand the second law of thermodynamics, which says that entropy (the property of matter that measures the degree of randomization or disorder at the microscopic level) can be produced but never destroyed (Reynolds & Perkins, 1977). The potential energy of our system, which is inversely proportional to its entropy, will decrease without the application of energy to our system. Stated another way, it states that "in a closed system, entropy always increases" (Bertalanffy, 1968, p. 144). But, as Mitchell points out, "nature gives us a singular counterexample: Life…According to our intuitions, over the long history of life, living systems have become vastly more complex and intricate rather than more disordered and entropic" (Mitchell, 2009, p. 71). The key is that living systems are *open systems*.

The second law of thermodynamics is true of all *closed systems*, those systems that exchange no materials with their environment. A car's fuel stores its potential energy; without refueling, the car will have a finite driving range. Similarly, our bodies store our potential energy; without consuming calories will cease to be able to function and eventually we will die. The flow of this energy maintains order and continued existence. There is no such thing as a perpetual motion machine; all systems are less than 100% efficient, and thus, they consume resources, requiring intervention from external entities, to remain viable. Open systems solve this entropy conundrum by exchanging matter with their environment. As a result, they can exhibit the equifinal behavior where "If a steady state is reached in an open system, it is independent of the initial conditions, and determined only by the system parameters, i.e., rates of reaction and transport" (Bertalanffy, 1968, p. 142).

If no energy enters or leaves a closed system, the potential energy of the system dissipates with time (i.e., its entropy increases). We can express this notion mathematically. If we designate entropy as S, then the change in entropy of a closed system can be expressed as follows:

$$\Delta S_C = S_{\text{final}} - S_{\text{initial}} \geq 0 \tag{11.3}$$

where ΔS_C = change in closed system entropy

S_{final} = final system entropy

S_{initial} = initial system entropy.

Open systems behave much differently, owing to their ability to transport matter in and out of the system. Their change in entropy, then, can be denoted as follows:

$$\Delta S_O = \Delta S_{\text{transport}} + \Delta S_{\text{reactions}} \tag{11.4}$$

where ΔS_O = change in open system entropy

$\Delta S_{\text{transport}}$ = change in entropy transport (either positive or negative) in and out of the system

$\Delta S_{\text{reactions}}$ = the production of entropy due to internal processes such as chemical reactions, diffusion, and heat transport.

The relevance of these two conceptualizations is that open systems can reach the same final state from different initial conditions due to exchanges with the system's environment (i.e., the principle of equifinality). This is directly relevant to us as we assess messes, which are open and involve significant matter (and information) exchange across their system boundaries.

The concept of entropy may be generalized to other contexts. Arguably, the most famous beside the thermodynamics perspective is physicist Ludwig Boltzmann's [1844–1906] statistical entropy (Boltzmann, 1905), which shows the relationship between entropy and the number of ways the atoms or molecules of a thermodynamic system can be arranged. Boltzmann's formula is as follows:

$$S = k_b \ln W \tag{11.5}$$

where S is entropy, as before, k_b is the Boltzmann's constant equal to 1.38×10^{-23} J/K, and W is conceptualized as the *thermodynamic probability* of a particular macro-state for some distribution of possible micro-level states of a thermodynamic system.

In a thermodynamic system where each state may have an unequal probability, it is useful to utilize a reformulation of this concept developed by J. Willard Gibbs [1839–1903] in his seminal work (Gibbs, 1902):

$$S = -k_b \sum_i p_i \ln p_i \tag{11.6}$$

where p_i refers to the probability that a given micro-state can occur. Claude Shannon [1916–2001], the father of information theory, adapted these concepts to the analysis of entropy in information, stating:

> That information be measured by entropy is, after all, natural when we remember that information, in communication theory, is associated with the amount of freedom of choice we have in constructing a message. (Shannon & Weaver, 1949, p. 13)

Shannon's conceptualization of information entropy, then, can be defined as follows:

$$H = -\sum_i p_i \log_{\mathrm{b}} p_i \tag{11.7}$$

where H is the information entropy, b is the base of the logarithm used (typically taken to be 2 due to the predominant use of binary logic in information theory), and p is the probability associated with each of the symbols in each discrete message i. It is worth noting that this formula is maximized when all state probabilities are equal (i.e., for a two-state system, $p_1 = p_2 = 1/2$). In this case, the most uncertainty possible is present in the system.

The question is, how is this energy handled by our system, be it information, thermodynamic, or statistical entropy? The short answer lies in the exploration of the concept of self-organization. Self-organization is a well-established phenomena in chemistry, physics, ecology, and sociobiology (Nicolis & Prigogine, 1977) defined as "the spontaneous reduction of entropy in a dynamic system" (Heylighen & Joslyn, 2003, p. 155). Recall our discussion of the second law of thermodynamics stating that entropy can be produced but not destroyed. How, then, is entropy in a system reduced?

Ilya Prigogine [1917–2003] received the 1977 Nobel Prize in Chemistry for his investigation, starting in the 1950s, of the case where self-organizing systems do not reach an equilibrium state. Nicolis and Prigogine (1977) were studying structures that they referred to as dissipative; these were structures that exhibited dynamic self-organization. As such, these open systems generated energy, which was dissipated to their environment. Thus, they were able to self-organize (i.e., decrease their entropy) by increasing the disorder (and thus, the entropy) of their environment. This is the key to survival for living systems; they reduce their internal entropy to avoid disorder and chaos prescribed by the second law of thermodynamics (and only true for closed systems). As such, these dissipative systems are able to maintain a dynamic equilibrium (D'Alembert, 1743) by dissipating their energy to the environment in an effort to create a reproducible steady state. This steady state can arise through multiple means, be it by system evolution, manufactured means, or a combination of the two. Examples of these systems range from purposeful systems such as climate control systems (i.e., heaters and air conditioners) to natural systems such as convection, hurricanes, and cyclones, to all living systems.

While these numerous examples illustrate the prevalence of self-organization, they do little to explain how or why self-organization occurs. The varying entropic perspectives of Nicolis, Prigogine, Boltzmann, Gibbs, and Shannon and Weaver are complemented by work in control theory and cybernetics. The term cybernetics was coined by Norbert Wiener in his seminal book whose title defined it as *the study of control and communication in the animal and the machine* (Wiener, 1948). Heylighen and Joslyn (2003), in a discussion of cybernetic control, speak of basins (Varghese & Thorp, 1988) and their relationship to self-organization:

> An attractor y is in general surrounded by a basin B(y): a set of states outside y whose evolution necessarily ends up inside: $\forall$ s $\in$ B(y), s $\notin$ y, n such that $f^n(s) \in$ y. In a deterministic system, every state either belongs to an attractor or to a basin. In a stochastic system there is a third category of states that can end up in either of several attractors. Once a system has entered an attractor, it can no longer reach states outside the attractor. This means that our uncertainty (or statistical entropy) H about the system's state has decreased: we now know for sure that it is not in any state that is not part of the attractor. This spontaneous reduction of entropy or, equivalently, increase in order or constraint, can be viewed as a most general model of self-organization. (Heylighen & Joslyn, 2003, p. 165)

The attractors described by Heylighen and Joslyn (2003) will end up in a state of dynamic equilibrium. This arrangement of elements and emergence of order are what W. Ross Ashby [1903–1972] called the *principle of self-organization* (Ashby, 1947). This self-organization results in a lowered entropy for our system as uncertainty has decreased within our system. Heinz von Foerster [1911–2002] devised the principle of *order from noise* (1960). Self-organization can be expedited by the presence of noise; the larger the random perturbations (*noise*) of a system, the more entropy exists in the system, and thus, the more quickly it will become ordered.

So, what does all of this mean? Our system changes, and maintains stability, as a result of mechanisms involving both evolution and self-organization. The order that emerges (both through evolution on longer time horizons and self-organization on shorter time horizons) is essential for our system to maintain its continued viability. We can enhance this viability through mechanisms such as those described by Beer (1979, 1981) in his Viable Systems Model. A self-organizing system achieves this viable equilibrium state by random exploration, with purposeful systems being aided by control mechanisms (recall Checkland's (1993) control principle), which reduce the feasible solution space (i.e., the variety) for these systems to explore. Ashby (1947), von Foerster (1960), and von Foerster and Zopf (1962) further postulate that this process can be expedited by increasing variation or noise into the system, thereby increasing system entropy and accelerating the systems search's for an equilibrium state. This process is confirmed by Prigogine's theory of dissipative structures, which increase their variation (and thus, entropy) until it is unsustainable and then dissipate this energy back into the environment.

What does this all mean for the systemic thinker? In theory, it provides a mechanism for determining when to interfere in our system; we should interact with it before its natural tendency to dissipate (or in Hitchins' terms, to decay or collapse) in an effort to expedite its search for equilibrium. In practice, this undertaking is not so straightforward as self-organizing systems, by definition exhibit behavior, as described by the *principle of homeostasis* (Cannon, 1929) in an effort to regulate their internal environment. Thus, the most practical approach for us is to identify application points or individual properties where a small change may result in a large, predictable effect. Accordingly, we turn to analysis of an approach which will enable us to determine an appropriate time for intervention in our system.

11.4 Another View of Sensemaking

Because complexity is such an important characteristic of systems, a number of frameworks have been developed for understanding the relationship between complexity and systems. One such framework is the Cynefin framework presented in Chap. 10.

Another way to look at the Cynefin framework is by the types of systems' connections expected to exist in each of the domains depicted in Fig. 11.6. Kurtz and Snowden (2003) discuss these connections:

> On the side of order, connections between a central director and its constituents are strong, often in the form of structures that restrict behavior in some way—for example, procedures, forms, blueprints, expectations, or pheromones. On the side of un-order, central connections are weak, and attempts at control through structure often fail from lack of grasp or

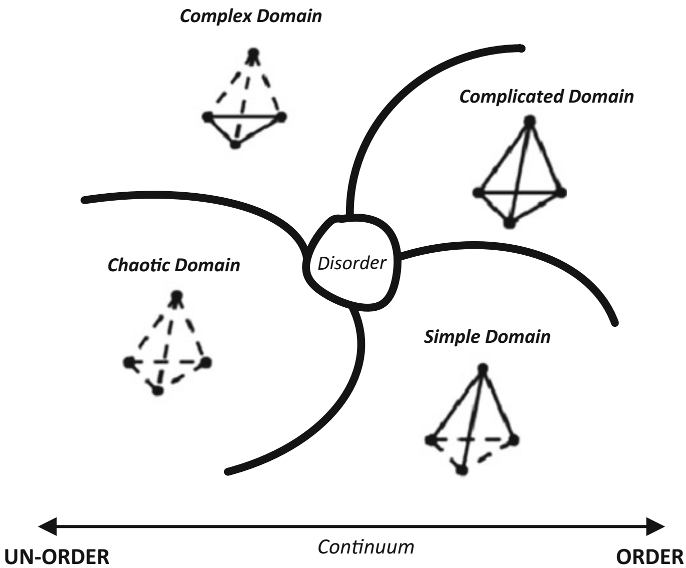

Fig. 11.6 Connection strength of Cynefin domains (adapted from Kurtz & Snowden, 2003, p. 470)

> visibility. In the complex and knowable domains, connections among constituent components are strong, and stable group patterns can emerge and resist change through repeated interaction, as with chemical messages, acquaintanceship, mutual goals and experiences. The known and chaotic domains share the characteristic that connections among constituent components are weak, and emergent patterns do not form on their own. (p. 470)

It is problematic for us to try to interfere in messes that reside primarily in the unorder domain (complex and chaos), both due to their weak central connections (in our terms, at the mess level) and their unpredictable and unperceivable relationships. It is our goal in these regimes, at best, to shift to an ordered domain. Here, we are invoking the *principle of relaxation time* (see Chap. 4), which sets the requirement for stability as a precursor to analysis and the need to avoid messes during periods of instability. Most importantly, we should concentrate on utilizing our resources to effect changes in the order domain, if possible. Kauffman (1993) echoes the difficulty in intervening in chaotic systems:

> Deep in the chaotic regime, alteration in the activity of any element in the system unleashes an avalanche of changes, or damage, which propagates throughout most of the system (Stauffer, 1987). Such spreading damage is equivalent to the butterfly effect or sensitivity to initial conditions typical of chaotic systems. The butterfly in Rio changes the weather in Chicago. Crosscurrents of such avalanches unleashed from different elements means that behavior is not controllable. Conversely, deep in the ordered regime, alteration at one point in the system only alters the behavior of a few neighboring elements. Signals cannot propagate widely throughout the system. Thus, control of complex behavior cannot be achieved. Just at the boundary between order and chaos, the most complex behavior can be achieved. (p. 302)

An alternative way of conceptualizing conditions for interaction is presented in Fig. 11.7. This figure shows the relationship of entropy and self-organization when

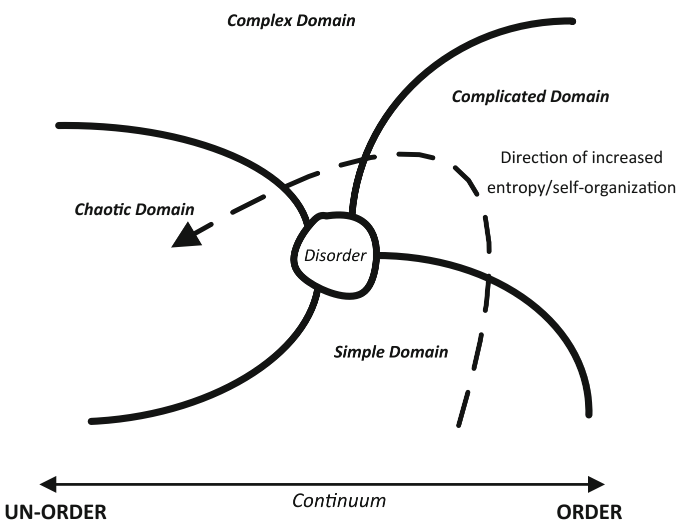

Fig. 11.7 Entropy and self-organization as applied to the Cynefin framework

compared to each Cynefin domain. As the underlying complexity of a situation increases, its entropy increases. This entropy feeds self-organizing behavior, which makes intervention problematic. Thus, it is advantageous for us to intervene in our system in the less entropic states (and set up conditions for self-organization, such as feedback mechanisms and regulators, in more entropic states).

How, then, should we intervene? This is the focus, in large part, of Chap. 10. *When* should we intervene in our system? We need to balance our desire for intervention (i.e., our bias for action) with consideration of the efficacy of our actions. For an answer to this question, we develop a decision flowchart for assessing intervention timing in the next section.

11.5 Decision Flowchart for Addressing *When* in Messes and Problems

Figure 11.8 shows our proposed decision flowchart for assessing if and when we should intervene in our mess in an effort to increase understanding about it. A discussion of the flowchart's elements is as follows:

Element 1 urges us to ask, *Is max(B/C)* $\geq$ *1 for our problem*? Put another way, is our system too mature? This question arises from the material presented in

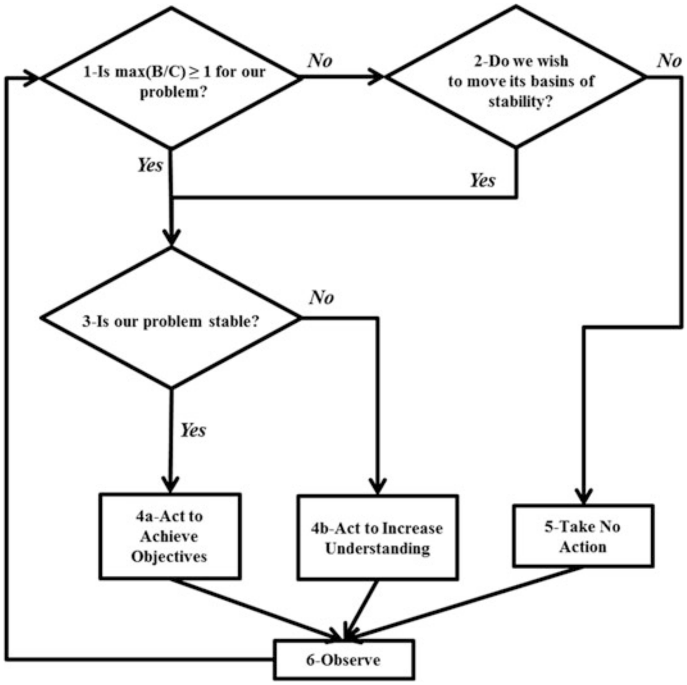

Fig. 11.8 Decision flowchart for assessing intervention timing

Sect. 11.1. The key here is asking whether or not our system has sufficient life remaining to warrant us expending resources to intervene in it. If it is too mature (*B/C* < 1), then we move on to Element 2. If not, we move to Element 3.

Element 2 serves as a follow-up to Element 1. If we have deemed the system too mature under its current configuration, the question we must ask ourselves is, recalling Varghese and Thorp (1988), *do we wish to move its basins of stability?* That is, do we wish to shift the system in a manner that perhaps renders it unrecognizable to observers previously familiar with it (see Fig. 11.5 and its shifted *B/C* curves to conceptualize the potential result of a shift in the system's basins, keeping in mind that intervention in a mess may result in either a positive or negative result). If the answer is no, we move to Element 5. If we do wish to alter it, we move to Element 3.

Element 3 encourages us to ask, *Is our problem stable*? While it is possible that no mess will ever exist here, we may decompose it further and explore its constituent problems. Stability can be thought of in the terms presented in Chap. 5; namely, if it exhibits simple or complicated behavior, then it is stable (or ordered, in Cynefin terms). If it exhibits complex or chaotic behavior, it is not (unordered in Cynefin terms). This can be checked by estimating current (i.e., unchanged) parameter values in our current scenario (using our FCM representation) and assessing scenario stability using a trivalent transfer function. If the scenario is stable, we should move to Element 4a. If it is not stable, we should move to Element 4b.

Element 4 (both 4a and 4b) represents our decision to act. Arriving here compels us to do *something*. Our resultant action is dependent on what effect we are trying to achieve, which is in turn influenced by the problem's stability. If we have a stable problem, then we can reasonably act to achieve our problem's objectives (*Element 4a*). If we have an unstable problem, we should act to increase our understanding about our problem (*Element 4b*). This action and its mechanisms are described in Part III of the text, starting with Chap. 12. While we offer no prescriptive advice regarding what action is to be taken at this point, we assert that an individual arriving at this element in the framework is compelled to do *something*. Failing to act, given the factors that led to this point, is likely to result in a Type V error (inaction when action is warranted). After acting, we move to Element 6.

Element 5 represents our decision not to act. If we have arrived here, our system, in its current form, is beyond help or we simply do not wish to try to salvage it. Thus, we choose to not act in order to avoid committing a Type IV error (taking inappropriate action to resolve a problem). This does not mean we are done with our mess; it merely means we will move on to observing without interfering with it. This stage continues to Element 6.

All elements eventually lead to *Element 6*. Element 6 asks us to observe. After acting (or not) based on the factors associated with our problem, we must observe the effects of our decisions. This may include waiting to see whether our mess becomes more orderly or attempting to realize the benefits of a programmed intervention in our system. Regardless of why we have arrived here, it is important to observe our system before the framework compels us to return to Element 1 and begin anew.

11.6 Framework for Addressing *When* in Messes and Problems

Addressing the *when* perspective in our messes and problems requires that we complete the following two steps for an identified problem:

1. Assess the problem FCM to ensure all concepts operate on the same timescale. If necessary, adjust causal weights to synchronize time steps.
2. Use the decision flowchart (Fig. 11.8) for addressing intervention timing to determine the appropriateness of intervening in a problem and to document the accompanying rationale.

A note on Step 1 is necessary before illustrating this framework on an example problem. Step 1 asks us to ensure that all causal weights are being assigned based on the same temporal scale (i.e., one day, one week, etc.) and adjust if necessary. We can investigate this notion by listing all concepts and their associated time period for change (i.e., a week, month, year, etc.). If all concepts do not change in the same time period, we can adjust *incoming* weights for those that do not synchronize them. We focus on adjusting incoming weights as they influence the speed at which a concept changes in our FCM. We can make adjustments as a rough order of magnitude by adjusting weights according to a reference point (e.g., the minimum time horizon in which a change in any concept in the FCM is observable).

More sophisticated techniques for dealing with temporal inconsistencies can be found in Park and Kim (1995), who add intermediate concepts to synchronize time steps between concepts and Hagiwara (1992), who provides techniques for incorporating nonlinear weights, conditional weights, and time delays between concepts. Each approach complicates the FCM development significantly and can be pursued if more sophisticated analysis is desired.

11.7 Example Problem

We return to our real estate example pictured in Fig. 11.9.

11.7.1 Timescale Assessment

First, we must analyze our FCM to ensure all concept transitions occur on the same timescale. We can list all of our concepts and their accompanying time horizon for change to ensure that they change at the same rate. This information is found in

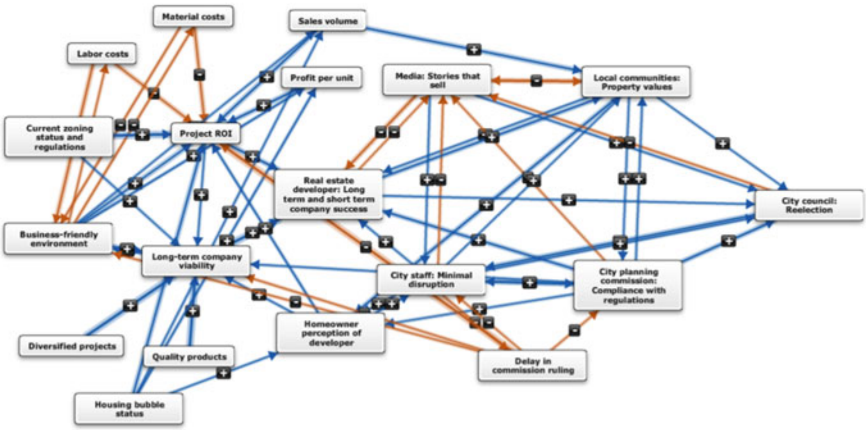

Fig. 11.9 Real estate example FCM

Table 11.1 Assessment of concept time horizons

Concept	Time period for change	Proposed change
City staff: minimal disruption	Weekly	None
Homeowner perception of developer	Weekly	None
Media: stories that sell	Weekly	None
Business-friendly environment	Monthly	–
City planning commission: compliance with regulations	Monthly	–
Current zoning status and regulations	Monthly	–
Delay in commission ruling	Monthly	–
Diversified projects	Monthly	–
Labor costs	Monthly	–
Material costs	Monthly	–
Profit per unit	Monthly	–
Project ROI	Monthly	–
Quality products	Monthly	–
Sales volume	Monthly	–
City council: reelection	Yearly	–
Housing bubble status	Yearly	–
Local communities: property values	Yearly	–
Long-term company viability	Yearly	–
Real estate developer: long-term company success and short-term company success	Yearly	–

Table 11.1. Note that proposed changes indicate whether the total magnitude of a weight should be increased (+) or decreased (−). An indication of two or more plus or minus values indicates a stronger temporal adjustment is necessary.

We can now adjust our causal weights using the information found in Table 11.1.

11.7.2 Intervention Timing

Armed with our modified FCM, we must work our way through the decision flowchart in Fig. 11.8. Starting with Element 1, we can definitively conclude that the benefit remaining in the problem (as it pertains to financial return) certainly outweighs the cost of intervention. So, $\max(B/C) \geq 1$. Next, we must ask whether or not our problem is stable (Element 3). This requires us to consider initial values for our concepts as the status quo. In this case, we believe *compliance with regulations* is at 1.0, while all remaining concepts are at 0 (absent any further information). The results of this analysis are shown in Fig. 11.10.

Clearly, the scenario is stable, but complicated. In this case, we move to Step 4a, *Act to achieve objectives*. Thus, overall, we can conclude that the problem has sufficient time to act and is stable enough to warrant action to resolve its objectives.

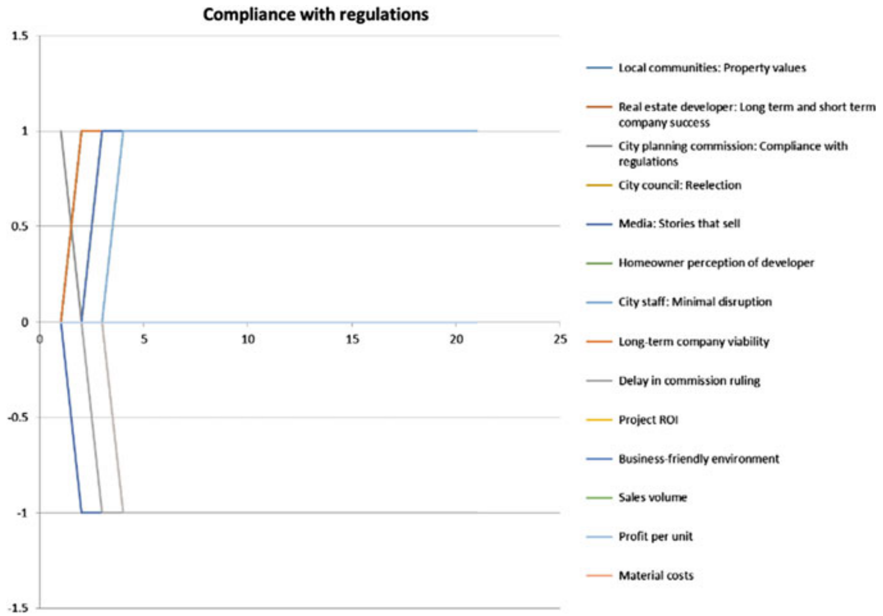

Fig. 11.10 Stability analysis of real estate example

11.8 Summary and Implications for Systemic Thinking

This chapter discussed the *when* question of systemic thinking. Thinking about this compels us to determine the appropriate time for us to intervene in our system, if ever. In order to develop an approach for determining the appropriate time for intervention in our mess, we developed an approach to assess the *maturity* and *stability* of our mess. The maturity discussion focused on life-cycle concerns and on evaluating the cost-to-benefit ratio of mess intervention, while our stability perspective focused on a discussion of system evolution and self-organization, leading to a method for classifying and understanding our system's state. We then combined these concepts into a six-element framework to serve as a guide for individuals interested in increasing understanding about their mess. After reading this chapter, the reader should

1. Be able to assess the maturity and stability of a problem; and
2. Understand the appropriateness of intervening in a given mess.

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