Working Paper

A Complex Systems Agenda for Teaching and Conducting Policy Studies

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Abstract

The teaching and conduct of policy analysis need to be updated to account better for the special challenges that arise because social problems often occur in *complex adaptive systems*. This working draft suggests a number of changes in pedagogy and practice relating to (1) worldview when conceiving and posing problems, (2) the basis for reasoning and inference within a worldview (i.e., the relative role of theory and data), (3) analytic style for conducting inquiry (e.g., treatment of uncertainty and the way in which options are compared) and (4) the character of the models used (e.g., analytic, system-dynamics, and agent-based models) and the questions asked of them. The working paper was developed to elicit reactions and suggestions from the communities involved with policy analysis, policy-related modeling (including computational social science), and the study of complex adaptive systems.

1 Introduction

1.1 Purpose

It has been 30-some years since awareness of complex adaptive systems (CAS) burgeoned as the result of work at the Santa Fe Institute (Waldrop, 1992), but the realm of policy studies has not yet reflected adequately the new insights. We are rethinking such matters at the Pardee RAND Graduate School, which is transforming its approach to teaching PhD students of policy analysis (Marquis, 2019). This working paper presents for discussion with communities of policy analysts, modelers, and researchers a tentative set of complexity-related items on which changes in teaching and practice seem important. Such changes in teaching are needed to prepare students for the complexity of policy issues that they will confront throughout their careers. For many aspects of policy studies, tried-and-true methods and mindsets will remain apt, but we focus on where change is warranted.

Although not discussed here, a related transformation underway in our graduate school is having a specialist stream dedicated to effecting real and sustainable change, in part through partnering with communities. It is not enough to *appreciate* a problem and analyze options. It is necessary to *act* constructively in designing, choosing, and implementing options over time as emphasized fifty years ago and in a later 30-year retrospective (Checkland, 1999, p. A5). Doing so is challenging for reasons tied to the complexity theme of this paper.

In what follows we first define our terms for discussing CAS; in Sections 2-5 we then consider issues relating to (1) worldview when conceiving and posing problems, (2) the basis for reasoning and inference within a worldview (e.g., the relative role of theory and data), (3) analytic style for conducting inquiry (e.g., treatment of uncertainty and the way in which options are compared) and (4) the character of the models used (e.g., analytic, system-dynamics, and agent-based models) and the questions asked of them.

1.2 Definitions

We use the term complex adaptive system (CAS) to refer to systems with nonlinear interactions involving adaptive *animate* components that lead to emergent properties uniquely characteristic of macroscopic levels (e.g., a sense of community).[1] These characteristics are not describable in the terms associated with more microscopic levels. We see CAS as a subset of complex systems more generally. Such systems may have emergent properties but need not have animate elements.[2] Table 1 summarizes the way we distinguish in this particular paper among simple, complicated, complex, and complex-adaptive systems. Definitions vary across the literature.

Table 1 Distinctions Among Types of System

Characterization	Numbers	Nonlinearities	Adaptive elements	Emergent phenomena	Examples
Simple system	Small	No	No	No	A printer-computer system with plug-and-play
Complicated system	Large	Yes	No	No	Troublesome furniture or barbeque grills to be assembled; intricate assemblages
Complex System	Usually large	Yes	No	Yes (may be due to inanimate features)	Modern automobiles and aircraft; dissipative systems in chemistry
Complex adaptive system (CAS) (subset of complex systems)	Usually large	Yes	Yes	Yes (due to animate agents or corresponding artificial intelligence agents)	Human body, social organizations, nations

As a side note, we do not characterize complex systems as “systems that are more than the sum of their parts” because most or all systems have this property.[3] That is why they are called systems rather than collections. An automobile is not an automobile without its propulsion, steering, and braking subsystems: the automobile's functionality is zero if any of these are absent, a nonlinear relationship.

2 Worldview

Our first agenda item is worldview. The worldview of the analyst, the way he or she views a problem, has a profound effect on the resulting study. We touch on issues related to system thinking, confronting complexity in CAS, and seeing decision making as a continuing process reflecting values and objectives, knowledge and uncertainty, and limits on the degree to which it is possible to control systems.

2.1 System Thinking

The first of our tentative admonitions is not very tentative: we should teach future policy analysts to see the world in system terms. System thinking is a holistic understanding of a system's parts, relationships, and processes. As an example, a systems approach to improving education would consider not just class size, but, e.g., the quality of teachers, curriculum, teaching materials, the physical character of the school, the safety of students in school or in transit, parent involvement, the home environment, and the way in which education is viewed by the community. A systems approach also includes paying attention to the system's environment and other aspects of context. Doing so is aided by viewing the problem through such different frames as material, social, and mental lenses (Pendleton-Jullian and Brown, 2018b).

The need for systems thinking was stressed decades ago with the advent of systems analysis and policy analysis (Quade and Boucher, 1968; Quade and Carter, 1989; Walker, 2000), System Dynamics (Forrester, 1963; Forrester, 1971; Sterman, 2000), and related methods (Dörner, 1997). Nonetheless, system thinking is often not visible in modern-day policy studies. It should be—to enable policy practitioners to better understand the issues and the mechanisms of how to bring about real and sustainable change.

Transformational change of a system may *emerge,* perhaps after changes initiated at levels where human beings have agency—i.e., the capacity to influence the system. Those human actions interact with other aspects of the system, including top-down and mid-level policies and constraints. The changes may occur as sequential increments over time, or may be more rapid. Bringing about beneficial transformations requires fearlessness along the way—designing, doing, learning, adapting, and often trying new ideas (Pendleton-Jullian and Brown, 2018b (Chapter 11)).[4]

2.2 Confronting Complexity and Wicked Problems

More than reemphasizing the system view is necessary. Policy analysis is mostly about *social* systems, usually complex adaptive systems (CAS). Seldom, however, does current policy analysis represent the emergent behaviors that loom large in CAS thinking. Econometric analysis, for example, highlights elasticities in a stable system without contemplating how new incentive structures can spawn such changes of organization and process as the rise of the order-from-Amazon economy and the collapse of department stores and shopping malls. These occur as people adapt to new technology and new circumstances.

Recognizing systems and adaptation is still not enough. The problems in policy analysis are not like those of physics and engineering: instead, they are often *wicked* problems. These are problems that are difficult to define and that are inherently unsolvable in the usual sense (Rittell and Webber, 1973). When wicked problems are successfully addressed, it is not because "the" solution is identified but because stakeholders have eventually agreed on compromise actions that will be good enough for all to tolerate even though many initial stakeholder objectives were not met. This is the stuff of *soft system methodology* (SSM) or *soft OR (*Checkland, 1999; Rittell and Webber, 1973; Churchman, 1961; Ackoff, 2008; and Rosenhead and Mingers, 2002). The practice of policy analysis in the United States has lagged in dealing with soft system issues, but related matters have been championed in the language of learning organizations (Senge, 1994; Schoemaker, 1995), system thinking for social change (Stroh, 2015), and dancing with systems (Meadows and Wright, 2008) (Chapter 7).

2.3 Decision making as a Continuing and Messy Process

Another aspect of analyst worldview is how decision making is conceived. Policy analysis often proceeds as though a single decision is to be made. Many social systems, however, change over time, sometimes abruptly and in surprising ways. Major course corrections may be necessary and management of CAS should be conceived with this mind. Some might relate this to the incrementalistic approach of "muddling through" (Lindblom, 1959; Lindblom, 1979), but we relate it to planning for adaptiveness. Teaching related skills is very different from teaching how to optimize a problem given fixed assumptions. Such planning can include scheduling branch-point decisions and building capabilities that allow responses to unpredictable developments (Davis, 1994, 2003) or the use of *dynamic-pathway* and related methods (Walker, Haasnoot, and Kwakkel, 2013). Adaptive strategies can be compared as a function of possible developments and a measure of *regret*, a subtle concept definable in significantly different ways (Groves et al., 2019) (pp. 33-34).

These methods anticipate surprises, some happy and some disappointing, and a *sequence* of actions over time that are likely to be troublesome. Progress is possible, but the process may be prolonged and messy. This is a very different image of decision making than one of study, decide, act, and be done with it.

2.4 The Values and Objectives That Drive Decisions

Whether at the beginning or along the way, decision making depends on judgments about how to improve matters. Typically, these are discussed in terms of utilities, which are seen as core concepts in traditional policy analysis, part of a unifying theme (Nyblade et al., 2019). That said, stakeholders often do not know their utility functions and no such utility function may even exist. After all, the concept of utility function depends on the stability of values, but values evolve as the result of experience, events, and challenges. A corporation may come to value its employees' quality of life; union members may come to value their company's commercial success. Nations may come to value strategies that are at once tough for deterrent purposes but also not threatening to other countries.

Values inform the objectives and goals (terms that are sometimes used interchangeably) set when making policy choices. Some are broad (e.g., better health for Americans), whereas others are more specific (e.g., making prescription drugs more affordable). Conceiving objectives in multiple levels is necessary—to see both forest and trees and to establish concrete objectives at different levels of detail, as in the U.S. defense department's strategies-to-task approach (Kent and Simons, 1994; Rhodes et al., 2007). A difficulty is that collections of clearly-stated, seemingly unobjectionable value-laden objectives often harbor deep conflicts or unresolvable trade-offs (e.g., data privacy vs. data utility, procedural fairness vs. equality of outcomes).

In classic policy analysis, "the" objective may be seen as a composite utility to be optimized. In a world of complex problems, however, we have multiple objectives that are often in tension and controversial. Compromise is about balancing considerations acceptably, not optimizing.

2.5 Knowledge, Uncertainty, and Disagreement

Decision making depends on knowledge. Policy analysis often proceeds as though much is known and only a few items are uncertain enough to worry about explicitly. This is simply wrong. The uncertainties in policy problems are frequently ubiquitous, large, and not amenable to best-estimate analysis. This was noted early in defense planning (Davis, 1994; Davis, 2014), in a visionary technologist's paper offering new ideas about reforming policy analysis (Bankes, 1993), and in climate-change studies that led to powerful new methods (Lempert et al., 2003; Groves and Lempert, 2007). A core concept from the 2003 study is that of *deep uncertainty*, defined as follows:

> Deep uncertainty: the condition in which "analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models, or (3) how to value the desirability of alternative outcomes." Confronting deep uncertainty alters one's world view and the way one goes about policy analysis, in both defense work and social-policy studies.

2.6 Moderation in the Search for Control

As a last item on worldview, we note that past generations of policy analysts have been trained to think in terms of top-down interventions with more or less predictable consequences.

For those sensitive to the character of CAS, the way ahead will be seen as more treacherous and the very concept of control should be approached with humility because consequences of interventions will often be surprising and sometimes distinctly counterproductive.

This has implications for implementation. Although the need for monitoring and feedback has long been recognized (Cyert and March, 1992), implementation has often been seen as a separate, pedestrian, and less prestigious subject by policy analysts. If, however, we expect to be surprised and dismayed by some of the consequences from interventions, we should be vigilant in watching for troublesome indicators and prompt in adapting efforts appropriately. Expertly guided adaptive implementation then becomes part of sequential decision making. National governments are notoriously ill-suited for rapid adaptation, so this will probably require more decentralization of interventions to states, communities, non-government organizations (NGOs), and commercial companies.

3 Basis for Reasoning and Inference

Given a worldview, how does an analyst reason about a problem?

3.1 Theory, Data, Association, and Causation

Discussing the basis for reasoning and inference highlights a long-standing schism between those who study policy problems with the statistical tools of social and health sciences and those who are more dependent on theory-building, as in assessing what military capabilities will be needed for future wars or how to change incentive structures to bring about changes in the health system amidst technology changes. The schism can be described, roughly, as data-driven versus theory-driven inquiry and is described elsewhere (Davis and O'Mahony, 2019, p.23).

Much current policy analysis for social problems is based on data-driven econometrics and other forms of statistical analysis. An example is evidence-based decision making, as when the efficacy of health treatments is judged by data from randomized control trials (RCTs).[5] This is in contrast with policy analysis that considers alternative future scenarios when evaluating options. For example, future military force structures are evaluated in simulated future conflicts. Similarly, corporations use scenario planning in strategic planning (Schwartz, 1995; Schoemaker, 1995). Empirical data is used in these but can play only a limited role because empirical data on future wars or the consumer-product battlefield of 2040 is, let us say, sparse.

Both data-driven and theory-driven work have their place, but the ideal is a hybrid that includes theory-informed data analysis and theoretical work that draws effectively on empirical information. Making that kind of hybrid activity easier to pursue is a significant challenge for social-science modelers, technologists, and scientists (Davis and O'Mahony, 2019). An important part of meeting that challenge is CAS-sensitive teaching of causal theory (cause-effect reasoning, not to be confused with causal inference in statistics).

The need for causal theory transcends our concern about CAS. As discussed by Judea Pearl, correlational data has distinct limitations and many questions cannot even be asked without causal models of the phenomena in question. These include questions about the effects of alternative interventions or other policy actions (Pearl, 2009; Pearl and Mackenzie, 2018). Several other problems exist with the evidence-based focus in policy analysis, even without considering complexity. First, it may stifle innovation that seeks to try new things or the application of common-sense cause-effect reasoning about a new way to do things. Second, empirical data is sometimes misleading as evidenced by "once-in-a-century" storms now occurring annually. Third, the data may not be representative. Such problems have been described by an insider's critique of past efforts to promote evidence-based practices (Brooks, 2016).

Returning to the theme of doing better in dealing with CAS, the need for increased emphasis on causal system modeling should be evident because we seldom have adequate data to understand fully the effects of interventions in social systems. We need theory to anticipate troublesome feedbacks, possible instabilities, and other complications. Theory is also necessary to sort out ambiguous cause-effect directionality, which is common in complex systems.

3.2 Types of Theory

Another striking difference across disciplines with respect to reasoning and inference is the connotation of "theory." In the social sciences, myriad definitions exist, causing severe confusion (Abend, 2008). One definition is that theory is "a systematic set of interrelated statements intended to explain some aspect of social life" (Rubin and Babbie, 2009). Other times, the word refers merely to discrete hypotheses or speculations.[6] In yet another usage (and in everyday language), the word is often used disparagingly, as in "Well, in theory such and such should be true, but—of course—we all know that…" This is in contrast with usage in such disciplines as physics in which "theory" is deeply respected and refers to an integrative and coherent set of principles by which to understand knowledge in a broad domain. Interestingly, context is as crucial in physics as in social science, but in physics the variables defining context are understood and specified, with the cases being distinguished sharply. Doing so is more difficult but not impossible when context includes effects of culture, history, and personal experience. We see special need for increasingly good theories of the integrated and coherent variety.

4 Analytic Style

Analytic style has many dimensions, but we touch on issues relating to the false dichotomy between analysis versus synthesis, the meaning of rigor, the treatment of uncertainty and disagreement, the way options are compared, and the questions asked of models.

4.1 Analysis Versus Synthesis, a False Dichotomy

We use the term "analysis" to mean "a detailed examination of anything complex in order to understand its nature or to determine its essential features: a thorough study" (Merriam Webster on-line dictionary). In this meaning, analysis is not just about decomposition, despite the Latin roots of the word. Thus, we reject the distinction sometimes drawn between analysis and synthesis. *Good* analysis, in our usage, often requires creativity, integration, and synthesis. As discussed earlier, it requires a system view of complex problems.

Another troublesome term that arises is “reductionism,” which sometimes is seen as thinking narrowly about parts rather than the whole. We see "reductionism" as an important part of studying complex systems, as when Herbert Simon described the human body as a nearly decomposable system (Simon, 1996) with different levels (cellular, tissue, organ) and subsystems (e.g., circulatory, digestive). Studying those parts and their relationships and interactions is essential in understanding the whole, the human body. The most holistic of physicians, the internist, seeks to do so. Similarly, the system engineer must understand the components of the system being designed, particularly their functions and relationships to other components, to create a working system.

This said, it is sometimes more insightful to focus thinking on the whole and interactions at the level of the whole, rather than seeking explanation from below. Some social phenomena, for example are perhaps best understood without going into individual characteristics and behaviors. This is perhaps less different from other domains than is sometimes realized. Some scientists work at the thermodynamic level without ever discussing molecular phenomena, even though thermodynamics can be understood in terms of more microscopic phenomena. A clinical psychologist may engage a particular patient by discussing life patterns and behaviors, and how they can be changed, rather than going into psychoanalysis and childhood trauma. In the world of investing and perhaps even in the realm of national economic policy making, it is sometimes more pragmatic to react to system-level signals (e.g., trends in prices, wages, and employment) than to attempt to make decisions based on analysis of poorly understood microscopic causal relationships.

In summary, good analysis—even for CAS— will sometimes be more reductionist and sometimes more holistic. Ideally, these modes of thinking are complementary.

4.2 Character of Analysis: Quantitative versus Qualitative, and Matters of Rigor

4.2.1 Quantitative versus Qualitative?

Much was made in the early years of policy analysis about the importance of quantitative analysis. This was seen as an antidote to emotional and sometimes parochial arguments. It was thought to be necessary for rigor. The emphasis on quantitative work, however, had negative side effects because many important variables are inherently imprecise and difficult to measure (e.g., love, hate, loyalty). As noted early by Jay Forrester, ignoring soft variables is to assert that they have no effect, which is often absurd. Critiques of systems analysis and rational-choice theory have noted that early versions omitted discussion of values other than narrowly defined self-interest (Amade, 2003).

A related point is that qualitative considerations often are profoundly important in defining the context in which issues arise and policies are considered. What solutions are acceptable depends on the local culture and on history. Does the proposed solution fit a narrative that resonates in the community? If not, the solution seems likely to be resisted strongly.[7]

4.2.2 Rigor

A next issue is the need to re-interpret the concept of rigor. Given the negative connotations of rigor (formulaic, austere, strict), perhaps we would be better off referring to "sound reasoning," but the word rigor will not go away. Thus, we believe that it should be interpreted to mean something like "logical, coherent, and the result of considering all relevant information" (a meaning familiar in philosophy). Such rigor is not necessarily quantitative or precise. Well-structured qualitative treatment will sometimes be sufficiently rigorous, as when dealing with CAS when behavior can be difficult or impossible to predict. Identifying approximate circumstances of instability will then be more rigorous than purporting to predict precisely when instabilities will manifest or, what forms the instability will take.

Modelers should aspire to contribute to theory development. This will mean constructing increasingly integrative theories to test in simulation for their relative ability to explain data, rather than comparing results across simulations based on simplistic theories.

A tradeoff exists between maximizing a kind of rigor when testing a narrow theory in a narrow context and instead seeking or testing broader theory for which some data is softer and less controlled. In our view, policy analysis needs relatively more emphasis on the broader constructs and system thinking. This, we believe, will increase the accuracy and relevance of conclusions to inform policy decisions, although sacrificing the rigorous statistical precision demanded in some disciplinary work.[8]

4.3 Confronting Uncertainty and Disagreement

A major characteristic of analysis is how it deals with uncertainty and also with disagreement, which can be seen as a type of uncertainty but merits being highlighted. Although system analysts and policy analysts have long noted the need for uncertainty analysis (Miser and Quade, 1988), it has long been given short shrift. The methods available have now improved dramatically. A first round of major advances introduced using probabilistic methods with subjective probabilities (Morgan and Henrion, 1992). A second round has involved addressing *deep uncertainty*, as defined in Section 2. We should encourage analysis that addresses the many kinds of uncertainty and disagreement from the very outset and as a matter of first-order attention. The result of policy analysis should often be identifying strategies that are flexible, adaptive, and robust—with no pretense of optimization. It has been argued that assisting policy makers in finding *FARness* should literally be an ethical responsibility of analysts (Davis, 2014). In different language, we should urge *robust decision making* (RDM)—i.e., seeking strategies that are robust in the broadest sense of that over-loaded term (Marchau et al., 2019).

This search for robust strategies may seem obvious, but consider how CSS practitioners often think about their simulation experiments. Do they develop their inputs and models so that, from the outset, all the important inputs can be changed readily, and so that model uncertainty can also be addressed (Davis, 2019; Davis and Popper, 2019)? Or, instead, do they hold nearly everything constant and focus only on variation of a few parameters? Doing better in this regard will be challenging with current infrastructure for computational social science. Technological innovation will be necessary. Part of this may involve adapting the benefits of certain high-level languages or tools that make uncertainty analysis routine (Analytica® and Crystal Ball® are examples). The other natural approach involves scenario-generation apparatuses for ensemble approaches, as discussed 20 years ago in a paper on computer assisted reasoning (Bankes et al., 2001). With super-computing, such use of ensemble methods is possible in near-real time (Groves et al., 2016).

Another concept is likely to be important in meeting the challenges. This is the concept of multi-resolution modeling (MRM). Given determination to do so, it is often possible for a modeling group to have an imperfect family of models at different levels of resolution (whether as a single program with switches or a family of related models) (Davis and Bigelow, 1998). It is then possible to do initial exploration at a high level (low resolution) with perhaps 3-10 variables and to then zoom into detail only where it is worthwhile to do so. This approach has been used successfully in a number of studies (Davis, 2014), but great opportunities exist for doing it better*)*.

Interestingly, and despite common impressions to the contrary, many policy makers are comfortable with planning under uncertainty. They value simulation-based analysis and interactive settings that helps them to understand connections and possibilities, and to view their problem area coherently. They have no illusions about the simulations being reliably predictive, but see them as something that might be called “policy flight simulators” (Rouse, 2015; Rouse, 2019).

4.4 Comparing Options

Early systems analysis highlighted cost-benefit and cost-effectiveness analysis (Miser and Quade, 1988). Later, some policy analysis came to emphasize multicriteria policy scorecards (Goeller, 1983) and to disparage “adding things up” because an option’s utility is often not a linear sum. Regrettably, that insight has often been lost and all too many studies (and government-mandated approaches) employ more formulaic cost-effectiveness methods. This practice should be supplanted because for those sensitive to CAS issues, it seems fundamental to distinguish among qualitatively different criteria and to recognize that the system behaviors of interest are related in nonlinear and sometimes incommensurate ways. This suggests that it should be routine to emphasize these matters and to show conclusions as a function of what are elsewhere called “perspectives” (Davis, 2014). Doing so may require effort. In the words of Adam Smith in 1759, still relevant centuries later (Smith, 1790, pp. part III, 2nd paragraph)

> We can never survey our own sentiments and motives, we can never form any judgment concerning them, unless we remove ourselves, as it were, from our own natural station, and endeavor to view them as a certain distance from us. But we can do this in no other way than by endeavoring to view them with the eyes of other people, or as other people are likely to view them… We endeavor to examine our own conduct as we imagine any other fair and impartial spectator would examine for it.

4.5 Changing the Questions Asked of Models

As a final element in this section on analytic style, we should discuss the questions asked. It has long been lore among policy analysts that defining the right question may be the most important part of a study. A related matter arises within any study using models: What questions should we ask of our models? In simulation studies in particular, it is standard to observe results (dependent on many, many input assumptions) and then to ask “What if?” questions. With each “What if?” a new simulation can be run, but that may require collecting or negotiating new data, making changes in the simulation program, and other time-consuming activities that may drag over months. If so, policymakers become impatient and disgusted.[9]

The way ahead is to think from the outset in terms of addressing broader, “Beyond-what-if” questions. Years ago, that phrase was introduced in the context of an approach that exploited simulations with PROLOG-style inference engines that would answer questions such as “Under what circumstances will we achieve our objective?” (Rothenberg and Narain, 1994). In today’s world, we can answer such questions with massive computational experiments and subsequent search for patterns in the results. This is referred to as “scenario discovery” in the toolkit associated with robust decision making (RDM) (Groves and Lempert, 2007; Marchau et al., 2019). In any case, we can and should now aspire toward analysis generating “region plots” and other mechanisms for preemptively addressing policymaker questions (Davis, 2019).

5 Character of Models and Model-Based Analysis

We have discussed worldview, reasoning, and analytic style. Let us now briefly discuss the models used in policy analysis.

5.1 Different Classes of Model

As we mentioned earlier, statistical models and methods have dominated social science and policy analysis, but we see the need for much more extensive use of causal models of various types. Many approaches are needed as discussed in two modern books (Cioffi-Revilla, 2014; Page, 2018). These may include analytical models, system dynamic models, agent-based models, network models among others. Also, research often benefits from using a combination of simple, mid-level, and detailed causal models; and various forms of human gaming (Davis, 2014, pp. 22-25).

5.2 Purpose of Models and Related Issues of Validity

Since models have many different purposes in research and policy analysis, it may seem evident that model validity should be assessed differently for those different purposes. This is well discussed in the System Dynamics literature (Sterman, 2000), but remains unappreciated. It is common to hear demands that models be “validated” as though that were a straightforward and unambiguous matter. Recent work (Davis et al., 2018) urges that the validity of models be assessed separately along dimensions of (1) description, (2) explanation, (3) postdiction, (4) exploratory analysis and coarse prediction, and (5) prediction. Many models are good for some but not others of these.

What do “explain” and “predict” mean in the present context? In the machine-learning community and the world of statistical analysis, “explanation” refers to the ability of a model to generate estimates that accord well with data, as measured by something like a correlation coefficient R^2. Good “explanation” may then refer only to the quality of data fitting. If the model can then generate results close to that of new data, it is said to be “predictive.” Neither of these meanings are suitable for policy analysts when talking with a policymaker. “Explanatory power” should then refer to the degree to which the model provides the cause-effect relationships that make the results understandable and actionable. Further, saying to a policymaker that a model is predictive should refer to future situations after the system reacts to interventions.

We should also comment briefly on internal, external, and measurement validity, core concepts in social science. Addressing CAS issues with cause-effect models addressing major uncertainties and disagreements will require different attitudes on these. It will be more important to get major phenomena roughly right and to anticipate possible negative consequences of intervention than to fit empirical data precisely. Measurement error will also be a bigger problem because some important variables are hard to define and even harder to measure. But omitting them, or pretending that they are represented adequately by more conveniently measured proxies, will be counterproductive. As merely one among myriad examples, GDP per capita is a poor proxy for understanding the economic well-being of the diverse people in a country. Measurement error is even more troublesome when outcomes important to stakeholders depend on context, history, and tacit cultural norms, including sacred values (Haidt, 2013).

5.3 Measures of Outcome from Models

Typically, the measure of outcome used in decision theory and policy analysis is the expected value (the mean) of some measure. Policy analysis has not paid adequate attention to distributional results. We should care not only whether the economy improves on average (e.g., as measured by gross national product per capita), but on how the benefits of that growth are distributed across segments of the population. Arguably, the focus on expected value has contributed to policies that have so disadvantaged the middle class as to be among the reasons for the political rebellions being felt in the United States, Great Britain, and elsewhere. As a related matter, the belief that "a rising tide lifts all boats" ignores the impact of the increased income disparity that often accompanies economic development.

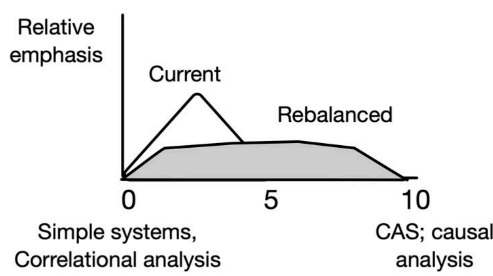
To those thinking about the implication of CAS for policy analysis, the need to go beyond expected value is probably even more evident. It is the nature of CAS to exhibit distributions at a given time and fluctuations, even sizable ones, over time. Furthermore, the very act of designating outcome metrics will motivate the system's self-interested adaptive agents to "game the metrics" by modifying their behaviors, sometimes in undesirable ways. This has been called Goodhart's Law, although it has many roots. Finding metrics resistant to such behavior becomes crucial. Such metrics can often be natural consequences of multi-level causal modeling (Davis, 2014).

6 Conclusions

Table 2 summarizes the paper. For each of the items discussed above, it suggests that an agenda for the teaching and conduct of policy studies should favor moving the relative emphasis from where it is now (the 2d column) toward something more CAS-informed (the 3d column).

The idea is indicated schematically in Figure 1 by depicting current and future coverage of the teaching spectrum from simple problems to CAS-sensitive thinking, using a 0 to 10 scale. Topics covered in the past remain important, but we see the need to extend coverage to the right—not to the extent of dwelling on complete chaos and related mathematics, but enough to appreciate the special issues of dealing with and managing complex adaptive systems, which includes keeping them away from chaotic regions.

Figure 1 Shifting the Balance of What Is Taught



Although the primary purpose of this paper is to present ideas about changing the teaching and conduct of policy analysis for reactions from a broader community, we also have suggestions for the practice of modeling, particularly computational social science (CSS).[10] These are discussed more fully elsewhere and relate to constructing models, infrastructure for exploration under uncertainty, extracting insights, and generating more informative results such as suggestions for strategy even when dealing with wicked systems. The opportunity exists for many forward-leaning developments. A number of related efforts have recently appeared (e.g., (Yilmaz and Ören, 2009; Yilmaz, 2019; Garibay et al., 2019), all of which are part of a recent edited volume on social-behavioral modeling for complex systems (Davis, O'Mahony, and Pfautz, 2019).

Table 2 Shifting the Balance in Policy Studies (A Straw man for Discussion)

Issue	As Seen Now	CAS-informed perspective
	Worldview	
Nature of system	Simple or complicated, perhaps complex but well behaved	Complex, adaptive systems, often not well behaved or predictable
Problems	Well posed, solvable	Wicked; solutions, if possible, to be emergent
Stability of system and decisions	Stable system, once-and-for-all decisions	Evolving system with continuing need for decisions to deal with developments
Values	Known, fixed, simple	To be discovered, complex, conflicting, changing
Objectives	Utility-based, as in a social welfare function or measure of military power; the best option optimizes	Multiple, often in tension; the best option balances considerations (including robustness of outcomes), but does not purport to optimize
Knowledge and uncertainty	Good, with some uncertainties	Deeply uncertain
Control	Top-down; direct; confident	Top-down, bottom-up, sideways; humble; indirect; iterative
	Basis for Reasoning and Inference	
Basis for inference	Data, correlation	Causal theory
Types of theory	Simple concepts motivating discrete hypotheses intended to describe and predict narrow phenomena in narrow contexts	Integrative and coherent set of principles describing classes of phenomena across many contexts (with explicit contextual distinctions)
	Analytic Style	
Character of "good" theory	Parsimonious in fitting empirical data accurately; dependent only on measurable variables	Rich enough to include important factors, even if uncertain and hard to measure
Uncertainty analysis	On margin as add-on	From outset, broad exploration
Basis for comparing options	Cost-effectiveness, cost-benefit	Multicriteria scoreboards; net effectiveness by perspective
	Character of Models and Model-Based Analysis	
Type	Statistical	Diverse causal models, games, and other methods (e.g., system dynamics, network, agent-based; as well as empirical methods)
Purpose	Explain and predict data in statistical sense (for stable systems)	Describe, explain (in causal terms), retrospectively predict, explore, and predict
Explanation and prediction	Meaningful correlations (R2) with old and new data	Causal explanation and prediction even as system and circumstances change
Focus of outcomes	Expected value	Distributional effects

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ENDNOTES

[1] "Emergence" has varied meanings and interpretations. Disagreements on the matter have a long history (O'Connor and Wong, 2015) and persist to this day (O'Mahony and Davis, 2019). Related papers discuss mereology, the study of the relation of parts to the whole (Varzi, 2019). A recent book discusses challenges of emergence for simulation (Mittal et al., 2018; especially, Tolk et al., 2018).

[2] A familiar example of emergence without animate system elements is sand grains assembling into a pattern of rippled dunes (Camazine, 2001). Less familiar examples include the Bénard cells arising from convection in a heated liquid (Nicolis and Prigogine, 1977) and the superfluidity of liquid Helium at temperatures below 2.1 degrees Kelvin (a quantum phenomenon). Emergent phenomena, including chaos, occur in some relatively small systems (e.g., 4-species predator-prey systems (Vano et al., 2006) and in Chua's electrical circuit (Matsumoto, 1984)).

[3] The greater-than-sum-of-parts description is often ascribed to Aristotle, but Aristotle actually said something like "...the whole is not, as it were, a mere heap, but the totality is something besides the parts..." (Cohen, 2016).

[4] As a military example, General Stanley McChrystal transformed the Joint Special Operations Center (JSOC) during the war in Afghanistan. His changes reframed the challenge as being no longer a fight for body count (a focus in Vietnam) but a fight for information. The resulting change in frame led to a strategic principle of "It takes a network to defeat a network," a principle anticipated earlier by scholars (Arquilla and Ronfeldt, 1996). Effects were profound militarily, although not enough to win the war.

[5] Data-driven researchers assess causality in terms of what explains past data, whereas the causal modeling we have in mind applies to circumstances and future not yet observed (Pearl, 2009). The subject of causality is deep and subtle, with many connotations (Cartwright, 2004; Halpern, 2016)

[6] Some exceptional figures see social-science theory more expansively. The philosopher Abraham Kaplan (a faculty member in the Pardee RAND Graduate School in the 1980s) saw theory as "a device for interpreting, criticizing, and unifying established laws, modifying them to fit data unanticipated in their formulation, and guiding the enterprise of discovering new and more powerful generalizations." (Kaplan, 1964, p.295).

[7] This point was emphasized speculatively in a February 2020 lecture at the Pardee RAND Graduate School by Steve Strongin, who lamented not yet having rigorous empirical data to support it.

[8] As an example, rigorous correlational research has shown that some states have been able to increase their minimum wages without a loss of low-paying jobs (Card and Kreuger, 1993; Cengiz et al., 2019). That, however, does not justify raising minimum wages generally. Policymakers need a reasonably sound theory that describes the circumstances under which raising the minimum wage would and would not have positive and negative consequences. Such theory might predict good consequences when profits are good and wage growth has lagged well behind productivity growth, whereas it might predict loss of low-paying jobs in other circumstances (Ritholtz, 2019). The data may not exist to validate such a better theory empirically, but it is difficult to have reasoned discussions and debate without one.

[9] Such dissatisfaction led to the U.S. Department of Defense disbanding a large analytic group that used complex "campaign models" routinely (Davis, 2016). That development should be a warning sign to all of those who gravitate toward trying to use big complex models as aids to strategic decisionmaking.

[10] Specialized versions of this working paper's first draft were presented at the October 2019 conference of the Society for Computational Social Science in Santa Fe, New Mexico and the November 2019 meeting of the Society for Decisionmaking Under Deep Uncertainty in Delft, Netherlands.