Towards Evidence-Driven Policy Design:

Complex Adaptive Systems and Computational Modeling

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ABSTRACT

Efforts to design public policies for social systems tend to confront highly complex conditions which have a large number of potentially relevant factors to be considered and rapidly changing conditions where continuous adaptation delays or obscures the effect of policies. Given unresolvable uncertainty in policy outcomes, the optimal solution is difficult, if ever possible, to nail down. It is more reasonable to choose a solution that is robust to as many future scenarios that might ensue from the decision. Arriving at such a solution requires policy makers to actively explore and exploit rich information to support their decision making in a cost-efficient, yet rigorous manner. We name this new working style as *evidence-driven policy design* and outline the characteristics of favorable evidence. We then argue that computational modeling is a potential tool for implementing evidence-driven policy design. It helps the study and design of solutions by simulating various environments, interventions, and the processes in which certain outcomes emerge from the decisions of policy makers. It allows policy makers to observe both the intended and, equally important, unintended consequences of policy alternatives. It also facilitates communication and consensus-building among policy makers and diverse stakeholders.

Keywords: policy making, evidence-driven, computational modeling, complex adaptive social systems

Introduction

Public policy problems represent complex adaptive social systems (Holland, 1992) in which many heterogeneous individual members act independently and interact with each other. The system is complex in that their global regularities are generated by decentralized local interactions of heterogeneous individuals. There is no uniform central control and the order is emergent. These environments are adaptive in that individuals learn and adapt to new policies over time and their new behaviors converge to develop novel collective patterns. Designing policies, and especially public policies, for such systems requires an understanding of individual

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behaviors which often cannot be simply aggregated or averaged and thus result in high complexity and uncertainty. Devising policies to dismantle terrorist networks provides a good example (Keller et al., 2010) of the associated complexities. Terrorist networks are complex entities that operate in a dynamic environment with a multitude of stakeholders each of whom has varying interests, motivations, action and resource sets, and goals. Designing and implementing policies for dismantling these networks is a non-trivial task. Some researchers (Fellman et al., 2003) suggest turning research attention to the "mid-range" (i.e., an intermediate or organizational level) instead of individual terrorists. However, understanding the behaviors of individual terrorists and their interactions, such as self-starter terrorism[2], are critical for creating socio-political environments that counter-act terrorism.

Designing robust policies for complex adaptive social systems is a real challenge for policy makers. According to Simon (1982: 66), problem solving is essentially information seeking through "a vast maze of possibilities." In theory, policy makers are supposed to go over all possible solutions and find the optimal one when they usually cannot because of the bounded rationality and computing capacity of human beings (Simon, 1957). Within the context of policy making, this "maze" is a multi-dimensional policy landscape of alternative solutions, which is defined by a set of relevant variables (each representing a dimension) and their interactions. The policy landscape of complex adaptive social systems is thus huge (a large number of variables and alternative solutions) and rough (optimal solution is obscured or overshadowed by various interactions among the variables). Designing policies in this context is a function of how effectively, and efficiently, individuals and groups can leverage information to make sense of the solution space.

Consider the case of dismantling terrorist networks effectively and efficiently. The information of terrorist networks is often collected by interviewing captured members, studying the policies of defunct terrorist groups, or examining the autobiographies of terrorists. While these methods provide a wealth of important information, we do not know whether, and to what extent, the information can be generalized beyond specific cases. Moreover, these methods are inefficient for capturing dynamic information on how terrorist networks morph and adapt in response to anti-terrorist activities (Sageman, 2004). Terrorist networks evolve even faster nowadays with the help of information technologies. To dismantle them, we must know the patterns of their formation and adaptation which indicate their vulnerability and resiliency to attacks. In addition, future terrorist networks are expected to span dispersed groups (e.g., Taliban, al-Qaeda, and Iraqi insurgents). The success of anti-terrorism activities will rely more on collaboration among, for example, different countries, military and civilian organizations, etc. Finally, predictive information is valuable due to the risk of unexpected consequences. A telling example is the Colombian drug cartels. The drug trade became even stronger after the major head Pablo Escobar was removed because the elimination of leadership made many cartels splinter into smaller, more flexible cells with the same motivations and similar capabilities. This outcome could have been avoided if there had been some efforts to predict the effects of the solution to solving the problem.

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[2] Terrorist acts that are carried out by small groups of individuals that don't seem to be recruited, directed, trained, or financed by any existing terrorist organization and form more or less spontaneously through the initiative of their members.

The above example shows the complexities associated with typical policy problems through the lens of complex adaptive social systems. Leveraging certain types of information (e.g., dynamic, customized, and predictive) is crucial for solving the problem. In this paper, we use the term *evidence-driven policy design* to indicate the policy-making process whereby policy makers actively explore and exploit evidence in support of their decisions, wherein *evidence* refers to the information that policy makers look to for decision-making. We argue that evidence-driven policy design is helpful for policy makers when they are dealing with complex adaptive social systems.

In the rest of the paper, Section 2 describes the nature of policy making for complex adaptive social systems. We then give a tentative definition of evidence-driven policy design and outline its features. Section 3 discusses the implementation of evidence-driven policy design by employing computational modeling. It is argued and illustrated that computational modeling is a viable approach to leverage dynamic, incomplete, and emergent information towards evidence-driven policy design. Section 4 concludes the paper and outlines areas for future research.

Towards Evidence-Driven Policy Design

In an ideal policy-making process, decision makers set clear goals, gather all necessary relevant information related to the problem and desired solutions, and then devise alternatives to meet goals. Alternatives are then prioritized and choices are made based on agreed upon criteria. This process is supported by accurate information, which reduces the uncertainties in policy making along with general theories, and guides the comparison of alternative solutions. However, this ideal approach is seldom witnessed when confronting contemporary policy problems.

First of all, rational comprehensive comparison is impossible for complex policy problems due to scalability issues (Lindblom, 1959). Policies for complex adaptive social systems focus on individual actors whose heterogeneity results in high value diversity and lots of policy outcomes (Kane, 1999). While a common objective is predefined, there remains considerable room for disagreement on sub-objectives. Although a policy solution is accepted, there will be disagreement on the specific way to implement it. Assessing those challenges with the intellectual capacities of policy makers, available information, and the resources (time, money) allocated to solve the problem makes it an impossible mission to go over all alternative policies based on all values to find the best one.

Secondly, the relevant values and policy alternatives often cannot be easily rated. As mentioned, disagreement is unavoidable in complex adaptive social systems. Coordination requires ranking incompatible values. Although the majority's preference seems to be a reasonable choice, it is often unavailable in reality because collecting information from a large number of stakeholders is costly. Furthermore, sometimes a small group of individuals' preferences should take priority over others' because, for example, they are influenced more by the new policy. Even if policy makers had a ranking of the values, comparing alternative policies could still be a problem. Since the outcome of a policy is a combination of different values, policy makers must figure out how much of one value is worth sacrificing for another in order to come up with a satisfactory policy. This may not be clear until one actually sees the policy outcomes.

Thirdly, the value ranking and the policy outcomes continue to change. In a complex adaptive social system, individual actors are able to adapt their behaviors to the dynamic environment (including new policies). The adaptation is progressive since bounded rationality prevents individual actors from finding the optimal strategy immediately. Moreover, there is mutual adjustment among different individuals as they interact with one another. These lead to complicated dynamism in complex adaptive systems over time. Therefore, robustness becomes a primary concern of policy making (Lempert, 2002), which requires an extensive exploration of internal and external factors that might influence the effect of new policies.

Due to the preceding reasons, policy design for complex adaptive social systems has a very different process than that of the ideal approach. First, the process is a practice of simplification. Policy makers disregard many values and policy alternatives as they are beyond present interest or not immediately relevant. They set up a principal goal and probably a few others that might compromise or complicate the principal goal. They explicitly or unconsciously outline a limited number of policy alternatives which are familiar from past experience. When comparing these alternatives, policy makers tend to rely on previous records or their own experience rather than general theories because the former are often more available and less demanding in data collection and analysis (Lindblom, 1959).

Second, the process is a successive, endless approximation to some desirable goals which themselves are open to change. As mentioned, not all values (which determine the goals) and policy alternatives are considered in practice. Policy makers choose a policy to attain some values and then select from these values. Such an intertwined and adaptive selection is more likely to be used because only the values of which the implementing policies differ need to be analyzed. In addition, dynamic environment may cause changes in values and policy outcomes. Social values and their ranking vary with specific situations. Technology development can improve policy prediction and trigger the re-evaluation of alternative policies. As a result, any new policy will only achieve part of the expected consequences and always produce some unanticipated outcomes. Therefore, policies should not be made once and forever, but revised endlessly.

Third, the process is a communication effort made by policy makers to convince multiple stakeholders. Assessing a new policy before implementation is particularly important for complex adaptive systems due to the complexity of problems, high cost of policy implementation, and the lag of feedback (global phenomena need time to emerge). As discussed, the entire policy-making process relies heavily on the experience and judgment of policy makers. The subjective and implicit nature of the process casts doubt on whether policy makers provide the best solution possible given all the limits of time, expenses, and their intellectual capacity. Moreover, since there is no central control in complex adaptive social systems, a large number of diverse, autonomous stakeholders compete over agenda setting and jurisdictions (Young et al., 2002). Thus, the assessment is less about outcomes and more about process and legitimation; trade-offs and negotiations are typical during the assessment process. Policy makers need to justify and defend their decisions by showing stakeholders evidence.

Evidence-Driven Policy Design

This section introduces the concept of *evidence-driven policy design*. We first distinguish it with *evidence-based policy making*, a topic that has been studied for years by researchers from the United Kingdom (UK) (Solesbury, 2001; Young et al., 2002). They intend to improve (social) policy making through broader use of existing scientific evidence. By *evidence*, they mean research findings which are scientifically rigorous. Policy makers are expected to systematically review and apply evidence when developing policies. We promote active information exploration and exploitation during policy making. In other words, policy makers are expected to create rich evidence by studying the problem, exploring alternative policies, and testing out solutions before they are actually implemented. We do not require the evidence to be rigorous or even correct, although certain types are more helpful. Policy makers are allowed to create evidence by themselves. From a knowledge management perspective, evidence-based policy making focuses on improving organizational performance with explicit codified knowledge, while evidence-driven policy design focuses on motivating individual actions of knowing and the evidence can be both tacit and explicit in nature. The former is thus inappropriate for developing policies for complex adaptive social systems. Since the process is characterized by change, complexity, uncertainty and ignorance (Lindblom, 1959; Schön, 1979), individual experience preponderates explicit evidence. The latter, on the other hand, does not have this problem. Table 1 summarizes the difference. However, we are inspired by the same belief that policy making could be improved by rigorously developing and using evidence, regardless of whether the evidence itself is rigorous or not.

Certain types of evidence are particularly helpful but barely available for the policy making within the context of complex adaptive social systems, which policy makers are recommended to explore or exploit. First of all, there should be evidence that explains the complex policy problem using a finite number of key factors. As mentioned, developing policies for complex adaptive social systems is a practice of simplification. Policy makers need to identify and keep primary variables and relationships while excluding other distractive details. It aids both policy makers and stakeholders in understanding the big picture and coming up with cost-efficient and widely accepted policies. On the contrary, comprehensive evidence is not only expensive (if ever possible) to get but also difficult to be propagated among a diverse group of stakeholders due to its high level of specification. For the same reason, it is inflexible and less useful in dynamic contexts. Both diversity and dynamism, however, are primary characteristics of complex adaptive social systems. Thus, comprehensiveness, in our view, should not be a goal when policy makers explore and exploit information on complex adaptive social systems

Table 1: Evidence-based policy making vs. Evidence-driven policy design

	Evidence-based policy making	**Evidence-driven policy design**
Nature of evidence	Explicit knowledge	Explicit or tacit knowledge
Policy-making process	Review and application of scientific findings	Exploration and exploitation of information, and scientific evidence
Purpose	Use existing evidence	Create rich evidence
Focus	Organizational performances	Individual actions

In addition, there should be evidence on the evolution and adaptation of the complex adaptive social system, such as non-equilibrium states and change drivers. They inform both the design and the assessment of policies by shedding light on intermediate outcomes (achieved goals and unexpected results) and future tendencies. Evidence predicting the future tendencies of complex adaptive social systems is particularly useful for policy design, but its accuracy and relevance usually cannot be guaranteed to account for irresolvable complexity and uncertainty. Nevertheless, it does not mean policy makers should not try to explore and exploit predictive evidence. Even though it may not help choose alternative policies, predictive evidence can still provide insights (whether true or false) into the conditions under which various policies are effective or not. For example, predictive evidence is often used to demonstrate how a policy may produce unexpected results or hypothesize and test out an explanation for a puzzling policy outcome (Bankes, 1993).

Finally, evidence should appear in a generic form yet still be easy to interpret by diverse stakeholders. Complex adaptive social systems usually have a variety of stakeholders – autonomous, heterogeneous individual actors or their groups – from whom intense debates on policy design are likely to occur. As mentioned, policy makers need to justify and defend their decisions. A policy-making environment rich in evidence can inform public debates which facilitate the development of widely accepted policies (Shulock, 1999). From a knowledge transfer perspective, policy debates are human interactions which involve exchange of knowledge and communication of meaning; the best performance is achieved when there is a moderate level of common knowledge or understanding among different stakeholders (Schilling et al., 2003). If we see evidence as the carrier of knowledge, it means new knowledge is better communicated when explained in a form familiar to the target stakeholder. Given the large number of stakeholders in a complex adaptive social system, an efficient way would be to assemble all evidence in a uniform framework which allows different stakeholders to “customize” the evidence to their own ends.

Evidence-driven policy design may seem difficult to implement in the past, but today there are an abundance of technical or social enablers, such as sophisticated technologies, unparalleled data access, and educated citizenry. Today, information technologies enable us to capture data at fine granularities and across a myriad of social and technical environments. In addition, data access is in the midst of a democratization process in terms of access and ability to leverage. As the citizenry of developed economies continue to take a more active role in the policy making and implementation processes, one can hope for richer and more creative debates around sound evidence in support (or in opposition) of policies being designed. In this paper we are interested in computational modeling and experimentation as a primary approach to evidence-driven policy design.

Computational Modeling as an instrument of Evidence-driven Policy Design

A computational model represents the behavior of a social system and is implemented by a computer program. It consists of a set of mathematical equations and/or transformation rules for the processes by which the variables in the system change over time. The aid of computers allows us to study complex, mathematically intractable processes. The modeler explores the behavior of the social system by conducting experiments on the computer program. Admittedly, this approach has just recently been applied in policy studies and practice (Yücel et al., 2009) despite a long history of use in natural sciences and the engineering domain. However, it is becoming more accepted because of the spreading recognition of its efficacy, the increasingly sophisticated modeling infrastructure, and the growing number of well-trained researchers and practitioners (Harrison et al., 2007). We argue that computational modeling supports evidence-driven policy design as summarized in Table 2.

Support Evidence-driven policy design

Validating the simplicity

A computational model is a simplified representation of a real social system and it often focuses on core theoretical components at the cost of peripheral details. Actually, no matter how many details we put into a model, it just will not have the same complexity as the real social system. Therefore, computational modeling as a tool for policy making has long been criticized for over-simplification, such as the neglect of factors that are hard to quantify and unrealistic assumptions (Cole et al., 1973). As a result, the interpretation of model results inevitably involves subjective judgments from the modelers (Bonabeau, 2002). True, these are all disadvantages of modeling, but only when realism and precision are the objectives (Bankes, 1993). Given that comprehensiveness and precision are not the objectives of evidence-driven policy design, simplicity should not become an obstacle for implementing evidence-driven policy design by computational modeling.

Table 2: Computational modeling in support of evidence-driven policy design

Features of policy making	**Evidence-driven policy design**	**Computational modeling**
Complex problems, intertwined factors, interdependent processes	Identify key variables and relationships	Validate the simplicity
Evolution and adaptation of both the system and individual actors	Unpack policy making process	Track the evolution
Inherent uncertainty, unexpected results	Examine various conditions	Explore the uncertainty
Communication (based on common understanding), Persuasion (based on the acknowledgement of diversity)	Assemble evidence in a universal framework but allow it to be specifically interpreted by various stakeholders	Involve the stakeholders by providing them with a standard yet customizable tool

Moreover, simplification is unavoidable and even useful for evidence-driven policy design for complex adaptive social systems, as we discussed above. In terms of computational modeling, the simpler the model, the easier it is to gain insight into the causal processes at work (Axelrod, 1997). For example, KISS (Keep It Simple Stupid) is a well-known model construction strategy which suggests starting with the simplest possible model then extending it step by step. Another example is agent-based models which generate complex, unexpected global regularities from local interactions in simple accepted rules (Macy et al., 2002). They are effective in exploring the generative mechanisms of complex adaptive social systems and thus very helpful for policy design.

However, we surely do not want to create an auto-referential formalization with nothing to do with the reality. Thus, key elements of the specific policy problem or the real social system should be identified and incorporated into the model. This is done by model validation, an indispensable part of almost all modeling-based studies. It usually has three steps— conceptual validation, implementation verification, and operational validation. Conceptual validation ensures the conceptual model represents the real social system and captures essential characteristics and behavior adequately in terms of the modeling purpose. The primary strategy is to decide how much the model should resemble the reality as early as the stage of model construction (Sargent, 2005) and to build the conceptual model based on existing theories or empirical evidence (Carroll et al., 1994). Implementation verification examines whether the computer program implements the ideas of the conceptual model. Operational validation concerns about whether model outputs (e.g., running time, outcomes of interest) are acceptably consistent with real data, previous modeling work, or the deduction of existing theories. It also examines the robustness of model results.

A valid computational model thus has sufficient details to address the research question while being simple enough to provide insights into the social system under investigation (Burton et al., 1995).

Tracking the evolution

Computational modeling provides detailed information on the evolution of the targeted social system. Since a model is implemented computationally, it is likely to keep track of the dynamic process and collect data on intermediate states, non-equilibrium conditions and internal and external drivers to changes. Then the modeler can rebuild historical changes of the social system, often by visualization, and predict its evolutionary tendency.

For complex adaptive social systems, it is also important to consider individual-level changes or the adaptive interactions of individual actors. As the terrorist-network example indicates, this is crucial to create an accurate description of the policy problem and, most importantly, to create a reliable forecast of how the new policy may affect the functioning of the system. "Without a model of the micro-foundations of emergent properties, path-dependent self-organizing processes are likely to be mistaken for institutions that are globally coordinated." (Macy et al., 2002) However, understanding individual-level dynamism is traditionally formidable due to the complexity.

One specific computational modeling, the agent-based modeling (Gilbert, 2008), is often used when individual dynamism is non-trivial for effective policy making. Carley (1990; 1991) examined group stability using an agent-based model in which individual agents interact, exchange information, adjust their socio-cultural position, and implicitly enter/exit groups. By analyzing the adaptive interaction process, the researcher found that the convergence of a simulated two-group society is not monotonic but oscillatory. Wu and Hu (2007) presented an agent-based model of E-government group behavior and showed how this model can help policy makers improve groups' acceptance of information technology (IT). They kept track of the level of IT acceptance in the simulated system and found that the initial IT acceptance level had little effect on future IT acceptance.

Exploring the uncertainty

The policies for complex adaptive systems must be robust to the inherent uncertainty. Thus, exploring system behavior in different conditions is a key component of evidence-driven policy design. Computational modeling supports systematic exploration by use of simulation experiments of which the results can be analyzed using statistical methods and visualization techniques.

A complex adaptive social system usually has a variety of interacting variables and multiple interdependent processes operating simultaneously. It tends to exhibit global behavioral patterns which are non-linear, stochastic, or subject to what-if scenarios. To understand the complexity, one can conduct simulation experiments which treat the computational model as a black box and examine the relationship between model assumptions, inputs and outputs. Thereby we can bypass model details which may not always be understandable and focus on exploring model behavior at the first place. In addition, simulation experiments are well controlled in that model outputs are purely determined by explicit and modifiable model assumptions and inputs preset by the modeler. Policy makers thus can test out tentative policies under a wide range of conditions and scenarios by systematically varying model parameters (separately or together). Other research methods such as sample survey or interview often need to deal with confounding factors, and they can only capture the state of the real world but cannot manipulate it.

An example is making organizational policies on exploration and exploitation (Fang et al., 2010; Kane et al., 2007; March, 1991; Miller et al., 2006; Rivkin et al., 2003; Siggelkow et al., 2006). Exploitation refers to the use and diffusion of existing knowledge, which yields more certain and immediate returns and improves organizational performance in the short run. Exploration refers to the search for new knowledge, which leads to the discovery of novel knowledge and improves organizational performance in the long run. A balance between exploration and exploitation is often needed, but how to achieve the balance is uncertain and differs from one organization to another. Computational modeling has been used to study this non-linear relationship since the very beginning.

Involving the stakeholders

Evidence-driven policy design implicates that policy makers should defend their decisions by showing diverse stakeholders evidence. To arrive at an agreement, stakeholders need to understand how decisions were made and be convinced that they will benefit from the proposed policy.

A common understanding is hard to get when policies are designed for complex adaptive social systems since the policy making process tends to be implicit and unexplainable. In this situation, the communication of evidence amounts to the transfer of tacit knowledge. Effective tacit knowledge transfer asks for a social context in which the knowledge recipient learns by observing the knowledge source execute his/her tasks (Brown et al., 2001), which is policy design in our case. A computation model assists the policy maker through the entire process, thus having a lot of tacit knowledge embedded. By explaining the computational model to diverse stakeholders, policy makers can more efficiently transfer their tacit knowledge.

In addition, stakeholders can customize the computational model to their own ends by manipulating the parameters of interest and isolating other factors to discern relationships meaningful for them. From the model, each stakeholder can know about the new policy's impact on him/her, as well as how other factors or other stakeholders may interfere. In other words, the computational model itself becomes evidence.

Practical issues

Computational modeling and experimentation is an appropriate approach to evidence-driven policy design regarding some important practical issues of policy design. First is the ethical issue. Some policies, such as whether or not to require vaccination for specific epidemics, cannot be tested on real populations, but there is no constraint on testing them on simulated populations. Second, collecting data from computational models is much faster. We do not need to go to the field to observe certain phenomena or wait for an indeterminate length of time to measure the outcomes. Third, it is relatively easy to fit the budget by adjusting the scale of the model or the extent of specification. Finally, computational modeling and experimentation is a cost-efficient approach in terms of the continuing decline in the cost of computing devices and their increasing ease of use.

Consider an extreme example – making policies against potential bio-terrorism attacks with smallpox. Empirical research in this domain is constrained because a smallpox attack has never happened before and the smallpox virus has disappeared from the public population today. The usefulness of historical epidemic data is undermined by the dramatic change in human populations since the last smallpox outbreak several decades ago. In cases like this one, modeling seems to be the only choice.

Implement Evidence-driven policy design

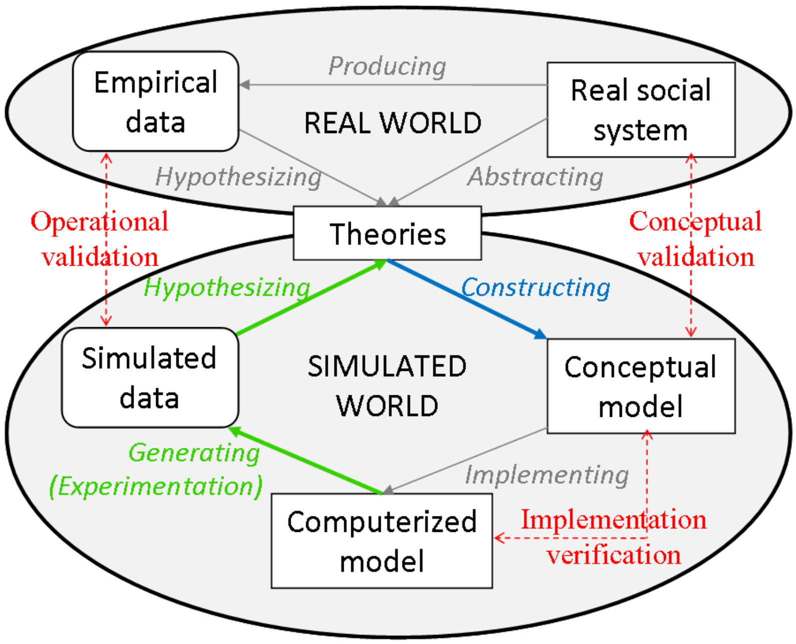
Figure 1, adapted from (Sargent, 2005) shows the process of evidence-driven policy design with computational modeling as the instrument. It starts with constructing a *conceptual model* which abstracts the targeted social system (blue arrow in the lower oval).

Model construction and conceptual validation

In this step, policy makers are required to: 1) identify key constructs and processes; 2) translate them into model variables and mechanisms; 3) set up model inputs and outputs based on specific policy problems; 4) specify assumptions that bound the inputs and outputs. The resultant model formalizes policy makers' perception of the policy problem and its potential solutions and thus should be valid.

Conceptual validation checks out the validity of the conceptual model by focusing on its consistency with empirical or theoretical evidence. However, there could be more than one piece of evidence on the same topic, and they may even contradict one another. In that case, policy makers are expected to be aware of and choose from alternative evidence. On the other hand, there could be no evidence at all. In that case, policy makers can use other techniques such as face validation and traces. Face validation has experts on the problem entity who evaluate the conceptual model to determine if it is correct and reasonable for its intended purpose. Traces track entities through each sub-model and the overall model to determine if the logic is correct and if the necessary accuracy is maintained.

Figure 1: The typical process and primary steps of a policy study based on computational modeling



Another important issue is the extent of abstraction. As mentioned, computational modeling supports evidence-driven policy design by providing "valid simplicity" and the conceptual model is essentially a search for balance between specification and generalization. There are different strategies for this purpose (Fagiolo et al., 2007). In addition to the KISS (Keep it simple, stupid) strategy that we have talked about, the KIDS (Keep it descriptive, stupid) strategy suggests beginning with the most descriptive model one can imagine then simplifying it as much as possible. Another strategy, TAPAS (Take A Previous model and Add Something), suggests developing from an existing model and then tweaking by strengthening or relaxing that model's initial assumptions.

Model implementation and implementation verification

The next step is to implement the conceptual model with a computer program, or so-called *computerized model*. Because of the inherent uncertainty of this type of social system, there is always something unexpected that needs to be distinguished from anything untrue. Moreover, unlike mathematical models which are presented as part of an article for publication, the programming code of computational models is usually not open to scrutiny in the peer-review process. It is critical, then, to make sure the computerized model behaves exactly as designed in the conceptual model. This is done by *implementation verification*.

Implementation verification intends to find out errors or artifacts that result in discrepancies between the computerized model and the conceptual model (Galán et al., 2009). An error refers to a mismatch between the conceptual model and the computerized model, such as the use of floating-point arithmetic[3] instead of real arithmetic (Izquierdo et al., 2006; Polhill et al., 2005; Polhill et al., 2006). An artifact refers to a mismatch between the expected and the real effects of an accessory assumption which are not representative features of the real system but added during the implementation to obtain a working computerized model. For example, agent-based modeling requires the modeler to define the structure of the interaction environment (e.g., grid or network), which will significantly influence who is going to interact with whom. To identify artifacts, policy makers are expected to make not only one but several alternative accessory assumptions and then compare their impacts.

Model analysis and simulation experimentation

In support of evidence-driven policy design, model analysis takes the form of *simulationexperiments*on the computerized model. The primary purpose is to explore the behavior of targeted social systems and the outcomes of proposed policies under various conditions. Specifically, policy makers manipulate model inputs (following rigorous experimental design) and analyze the corresponding model outputs. By doing so, they try to figure out any significant correlation between model inputs and outputs, as well as the details of the transformation from inputs to outputs. The former will become variance-based theoretical hypothesis, while the latter sheds light on building certain process theories. For experiments on complex adaptive social systems, model inputs are usually parameters that define individuals' actions or their interaction environment; model outputs tend to be global characteristics of the social system which are difficult to explicitly model or intuitively infer. The transform from inputs to outputs is thus a generative process that involves different levels. Given the frequent needs of and the difficulty in cross-level analysis, computational modeling and experimentation provides a powerful tool for policy makers.

Computational modeling and experimentation is also powerful in exploring the impacts of different scenarios on the targeted social system. Since explicit specification of conditional parameters is always required for simulation experiments, policy makers can systematically study certain scenarios by setting them as model parameters. The following conditional parameters are typical in computational models for complex adaptive social systems: the initial values or ranges of key variables, the initial setting of the interaction environment, and the duration of simulation (which can be a specific number of time periods or an established rule on when to stop).

Finally, model analysis is a process in which the model itself gets improved. The data from simulation experiments will be examined in terms of accuracy (for specific modeling purpose) and applicability (for specific domain) (Sargent, 2005). There might be a comparison between simulated data and real data if the latter is available, a process known as *operational validation*. Model variables that turn out to be insignificant will be removed from the model, while unidentified significant variables will be added to the model.

An illustration

We conducted a study which evaluates the effectiveness of various attack strategies on

[3] Floating point arithmetic is the standard way to represent and work with non-integer numbers in a digital computer. It is designed to create the illusion of working with real numbers in a machine that can only strictly work with a finite set of numbers.

terrorist networks by use of computational modeling (specifically, agent-based modeling) (Keller et al., 2010). The conceptual model consists of: (1) a set of agents linked in a network; (2) an anti-terrorism environment where attacks to the network occur systematically.

Each agent represents a terrorist, either a leader or a follower (grassroots), depending on how many connections it has as well as how long it has been a part of the network. Connections between agents represent their relationships and are built based on mutual agreement. Agents continually develop connections and they all prefer to connect with high-status individuals (i.e. those that are seen as leaders or those that have more connections than them) in the system. After two agents connect, the low-ranking agent will contribute some of its resources to the high-ranked agent; connecting will not happen if low-ranking agents do not have enough resources. We modeled this to account for how relationships are built within terrorist networks, i.e., where lower ranking agents either try to impress the network leaders through the execution of terrorist acts or offer up other valuable assets (e.g. information). Therefore, heavily connected ones will get even more popular and ultimately become leaders. This mechanism is consistent with that of the well-known BA model – new nodes attach preferentially to old nodes that are already well-connected.

Environmental “attacks” on the system remove terrorists as well as their connections, thereby disrupting the network. The model distinguishes four commonly applied yet simplified attack strategies. The leader-focused strategy removes leaders, while the grassroots strategy removes grassroots. The geographic strategy randomly chooses a local area and removes all agents in there. The random strategy removes a random selection of agents. Each of them has associated pros and cons and varying impacts on the structure and capabilities of a terrorist network.

The evaluation of attack strategies is conducted in two different scenarios, i.e., where the terrorists know or do not know about an impending attack on their organization. Having information of an impending attack affords the terrorist network to prepare for it, thereby limiting the effect of the attack on its structure and resources. Results obtained in this scenario can provide very important insights since it takes individual adaptation and system dynamism into consideration.

Model analysis generates some interesting hypotheses worth further investigation, such as:

- A mature[4] terrorist network is a stable structure in terms of connectivity.
- Resources in a terrorist network gradually converge to a few leaders as the network evolves even if early on they are dispersed among various agents.
- The grassroots-focused strategy is more effective when the terrorist network is in its infancy or its fully developed stage.
- In a mature terrorist network, the number of leaders is reliably small and the leaders are relatively inactive.

[4] This is a state when a few leaders own most of the connections but refuse to accept more, while the majority of agents only have a few connections and little chance to become new leaders.

* The leader-focused strategy reaches its peak performance when the network is still growing. At this stage, a relatively large number of candidates compete for the leadership roles by continuously attracting connections from others (recruiting more followers).

Each of these results suggests evidence that need to be carefully considered as policy-makers undertake the difficult task of arriving at robust solutions. While none of the above evidence suggests a given policy outcome that one must implement, they provide discussion points for rich, evidence-driven, rather than ego-centered, policy deliberations. In addition, as policy options are designed their efficacy can be put through rigorous testing by leveraging the computational environment.

Conclusion

Developing policies for complex adaptive social systems can be extremely difficult. In these settings, the goals are often ambiguous and the means to achieve them are uncertain. The problem to be solved is complex and represents a moving target. Information is never conclusive but reflects the indeterminacy of cause and effect relationships. There are diverse stakeholders who need to be involved. Thus, policy makers rely on their own hunches and experiences to arrive at solutions. The policy making process appears to be subjective and implicit, leading to suspicion on the proposed solutions. Moreover, in many cases, the solutions are brittle, leading to weak implementations.

We suggest that policy makers systemize their practices as much as possible to justify and defend their decisions. The primary strategy is to proactively search for and leverage information (as evidence). Useful information will indicate a small number of key variables and mechanisms within the target social system, unpack the evolution of the system, and facilitate communication among policy makers and various stakeholders. We argue that computational modeling is a promising approach to evidence-driven policy design in that it can provide an environment to manage the above-mentioned evidence towards designing robust public policies. Evidence-driven policy design is underpinned by robust and optimal management of information towards solving complex problems. Within this approach, the complexity of problems is seen as an opportunity to be innovative in how information is managed within the policy design process. To this end, it is essential that we leverage the advances in computational technologies and approaches that are capable of capturing, synthesizing, visualizing, and interpreting massive amounts of information across a wide spectrum of forms, functions, and origins.

As future research, we can consider building technologies and platforms that facilitate evidence-driven policy design, for example, an exploratory environment that allows users to navigate efficiently through the space of plausible models and model outputs to construct lines of reasoning and to learn about the implications of hypotheses. There is also a need for research on how simulation environments and outcomes influence policy decisions (do they make any difference in decision-outcomes, etc). To this end, we suggest that research be conducted on how policy makers perceive, and interact with, simulation environments. Finally, we suggest that as a community, public policy and administration need to embrace the role of information-rich (i.e. policy informatics) solutions and a research lens on critical problems facing our society.

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