The Future Engaging Complexity and Policy: Afghanistan Citizen Allegiance Model

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Abstract

With the world becoming more interconnected, interdependent, and complex, research needs to take into account the dynamism of interacting systems. Whereby traditional research methodologies have allowed for significant epistemological advances in policy studies, there remain opportunities to augment methodologies to account for emergence, rare events, tipping points, patterns, and processes found in complexity science. This research provides rationale, background, and policymaking considerations applying complexity science to policy studies research. To this end, we employ an agent-based model simulation of citizen alliance for the population of Afghanistan to demonstrate real-world application in policy studies. The flexibility of the model and its ability to change parameters demonstrate outcomes of varying policy scenarios. Additionally, the model tests the influence of Afghanistan news reports of insurgents attempting to gain influence by co-opting established leadership.

Keywords: Complexity, policy, complexity science, simulations, agent-based model

Overview of research and presentations

This work was done in collaboration with researchers at the Complex Systems Institute, Oak Ridge National Laboratories, and Georgia Tech. It was funded by DARPA MIPR 07-X029. The research has been presented to a variety of audiences from the business community to academic settings.

The Afghanistan model was formally presented at the 2008 Institute of Electronics and Electrical Engineers/Women in Computing/Association for Computing Machinery International Conference on Web Intelligence and Intelligent Agent Technology, December 9-12, 2008, Sydney, Australia.

Introduction

For responsible scientists contributing to the epistemological and ontological knowledge base of social reality, the primary goal of policy research should not only be to forecast the future, but also to add to our understanding of it and positively affect it. The authors of this paper want to be able to prepare for the risks and opportunities of future scenarios, of "what could be" when it comes to the current, volatile situation in Afghanistan and the social dynamics surrounding it.There continues to be ingrained scientific biases toward what researchers think is possible, plausible, likely, and desirable. It is critical to recognize that the imaginative perception of research possibilities is narrow and bounded by current cognitive horizons and constraints (Rescher, 1998). Given these biases, we question the adequacy of our current methodological tools and approaches to address an increasingly interconnected, interdependent, and complex world.Because social scientists face the daunting task of unraveling the mysteries of social phenomena within a context of interrelating systems and complexity, we employ complexity science theory broadly and agent based modeling specifically to expand on current conceptions of plausibility, likelihood, and desirability. Researchers in other disciplines have made significant progress utilizing theories and tools from complexity science, which is paving the way for policy researchers.

What is Complexity Science?

Complexity science provides a research framework to model social phenomena from a holistic integrated lens of dynamism and process. Its powerful research tools, the result of advances in computing platforms, provide an opportunity to move beyond traditional research that generally describes "what is," to a more critical inquiry exploring "what if" and "what could be." Yet there is currently no agreed upon definition of complexity science and what it encompasses. In fact, definitions and theoretical approaches vary both within and across disciplines.

Complexity science is based on the simple premise that the whole is greater than the sum of its parts. It is an interdisciplinary scientific study of complex systems. Complexity remains a subjective concept due to the inability to observe all interactions of social phenomena bias-free. Despite the lack of consistent definitions and unified theories in complexity science, the consensus view is that complex systems are usually made of many partsreferred to as elements, agents, or constituent parts. Theseparts dynamically interact with other parts and within a dynamic environment to influence their own futures. The combination of these parts interacting at the individual agent, or micro, level, gives rise to system-wide, global, or macro behaviors. The micro and macro level systems can influence each other while interacting within a dynamic environment. System-wide patterns can emerge from the interdependent interactions of adaptation from autonomous agents at the individual level.

The goal of complexity science is to identify consistent patterns, trends, and tendencies in the simulated reproductions of system behaviors so that appropriate strategies can be developed for system enhancement. Literature has shown that complexity science has been successful in studying physical phenomena in the fields of physics, biology, engineering, and neurobiology. Additionally, complexity science has been successfully incorporated into business, economics, ecology, transportation, healthcare, and defense research. We assert that policy researchers can now apply the discoveries and insights gained from studying physical systems to social system research, plus utilize gains from social science complexity research. Social, economic, and environmental systems are the major global systems within which sub-systems are nested (Johnson, 2010). These systems and their parts exhibit dynamic processes of mutually adaptive interactions.

Consequently, observable patterns can develop and be observed in research. Examining the behavior of dynamic social systems can provide insight into system trends in the form of patterns that would otherwise be unpredictable (Ogula, 2008).

The goal in applying complexity science to policy studies is to begin to understand and anticipate critical patterns in social systems to facilitate more effective strategies and better decisions for policy intervention and to prevent cascading system failures.Most of the pressing real-world challenges in policy exist in complex systems.Many of the advances in complex systems research has come from studying phenomena in physics, physical systems, networks, evolutionary biology, and chaos theory. These disciplines have shown that while phenomena can behave in a complex manner in time and space, we can ultimately know their underlying laws. In the case of complex human systems such as societies and global economies, the behaviors in time and space are complex, yet the systems are unpredictable because the underlying laws are unknown (Strogatz, 2008). With social systemsbecoming more complex, the science of complexity offers unique strategies to tackle some of the most challenging problems faced in policy research.

Rationale for Complexity Science in Policy Studies

Recognizing this state of the dicipline, we as researchers need to respond by adapting our thinking and approaches. As Einstein remarked, “We can’t solve problems using the same kind of thinking we used when we created them” (BrainyQuote, 2013).The time has come to examine complexity in the world and its impact on policy research through a new lens recognizing that everything that happens in the world is new, and the world does not repeat itself (Bar-Yam, 2010). Complexity represents and describes unique ways to think about mimicking, abstracting, and learning about the world. The optimal goal is to gain insight with complexity science simulation models while capturing more and more levels of system details.

Policy studies, like other social science disciplines, has been predominantly driven by empirical statistical research methods that attempt to describe and predict “what is” throughthe average of means, as well as more sophisticated methods of pseudo control groups versus treatment groups. The use of standard methods of quantitative and qualitative research has provided a wealth of knowledge, yet do not adequately account for complexity, interdependent systems, emergence, tipping points, patterns, and/or rare events. There are those in the social sciences who suggest traditional reductionist research methods already offer adequate means to predict the future and justify making informed decisions. While such approaches can explain parts of processes, they fall short in explaining the whole of phenomena interactions. Reductionist approaches often claim to explain whole systems and predict outcomes using linear techniques for non-linear social system dynamics. Non-linearity refers to systems that cannot be easily formalized into linear equations. There are a variety of social phenomena and social systems in policy research that fall into the non-linearity category. Non-linear systems are influenced by an unidentified cause or causes that researchers cannot characterize for reasons not yet discernable (Rescher, 1998).

Reductionism and isolated system approaches are not adequate to account for the processes and dynamism necessary for advancing policy research. Nor does it follow logically that valid inferences can be made by using results from isolated systems to make conclusions about complex, interacting, adaptive systems.As the classic example goes, no matter how many times you observe white swans, it does not justify researchers claiming that all swans are white (Popper [1959] 2008,p. 4).Given the static nature of traditional research and the dynamic nature of social phenomena, alternative approaches like complexity science can address such methodological shortcomings. Mathematical equation-based models can address many policy research problems. But traditional social science has limited tools to learn about the world, and so it can take us only so far.

Additionally, there are complex aspects of the social world that just could not be fully grasped or deciphered until recently. Social phenomena that include processes, interactions, patterns, and emergence require more than an insular approach.

The powerful computing tools of complexity now make the work of discovering the intricacies of complex systems in policy more tractable and understandable.

Furthermore, the new capabilities of research tools create shifting perspectives so that new questions about the world can be asked. With these exciting tools, researchers can open new scientific doors to expand the boundaries of what we can know about complex systems and therefore by extension about humans and our interactions(Bar-Yam, 2010).Complexity science offers novel ways to think about policy research that transcend traditional methodology and tools because a multitude of interactions can give rise to a social system that generates complexity, equilibrium, or chaos (Page, 2005). Complexity tools can provide the means for modeling a social system's transition into and through the states and phases of complexity, equilibrium, and chaos. We can then explore the decentralized mechanism of control in social systems, or what directs this still mysterious bottom-up self-organization process (Miller & Page, 2007). Complexity researchers can accommodate a system's ability to discriminate and react to the environment, respond to its own internal states, focus attention, and integrate information.

The key to translating complexity mechanisms into useful policy research is discovering how the system's parts interact and give rise to patterns. In some cases, even defining the parts of a system may be challenging. For example, it is not always obvious whether a phenomenon should be defined as an agent or an attribute of an agent (e.g., a patient may be either an agent or a property of an agent called person).The next step is to observe the dynamic relationships between the whole and its interdependent sub-systems. Social systems differ from physical systems in that people learn and adapt. In agent-based model simulations of such systems, people are represented as agents. Agents themselves can choose their level of connectedness, interdependence, adaptively, and responsiveness if endowed with such capabilities. Research attention should focus on evolutionary learning and dynamic connections in social systems to better understand macro system resiliency in the face of threats or challenges in the context of information flow, energy, and resources.

Incorporating a variety of tools can make theory better, according to Page (Miller & Page, 2007), and there is ample room in policy studies to improve theories. A triangulation approach that adds complexity to quantitative and qualitative research strategies can help address the gaps in understanding interconnected parts that are necessary for a better understanding of social phenomena. The potential of three integrated research approaches and strategies can help strengthen experimentation and the analysis of results. It is important to note that some social systems are complicated as opposed to complex, linear in nature, and predictable. Such social systems, although complicated,may be best served by traditional research approaches. However, complex social systems with non-linear interactions, self-organization, adaptations, and emergence characteristics require additional modeling techniques that complexity tools can offer. Social beings actively seek connections and adjust in response to environmental and social cues. Complexity tools can be structured to create simulations that capture these interactions and take into account the heterogeneity of people in the systems.

There are a variety of complexity tools to use in modeling policy research, and there are many advantages to creating models of system behavior with complexity. Complexity science tools include agent-based modeling, network analysis, data mining, scenario modeling, sensitivity analysis, and dynamic systems modeling. But beyond better insight and understanding of policy dynamics, there still needs to be better policy design and interventions in light of complexity. Complexity simulations can serve as policy labs where various policy interventions and various parameters of interventions can be modeled on complex system dynamics (Page, 2005). The simulations can reconstruct policy processes and explain historical iterations. Complexity research results can identify critical gaps in empirical data. Also the methods can support the reduction of alternative hypotheses or the rejection of those that do not match up to real system behavioral outcomes. The depth, breadth, and dimensions of policy research resulting from complexity simulations can offer multiple levels of analysis.

Social phenomena occur on multiple levels and merit multiple levels of explanation. For example, a Congressional vote can be explained as if it were a single event. The same vote can also be explained as an aggregation of voting actions.

Modeling solely single levels does not allow for sufficient analysis of network connections, feedback adaptation between levels, or the degree of influence on policy outcomes (Page, 2005). In single-level only research, it is possible to overlook policy synergies, emergent counterintuitive outcomes, and the possibilities that successful policy interventions in one area cancel out success with other interventions. Complexity methodology can address single-level analysis issues and more (Epstein & Axtel, 1996).

Epstein and Axtel (1996) assert that social sciences are a difficult research area to work in because there can be a multiplicity of interactions in social systems that create further layers of complexity. Furthermore, the sub-processes of social sciences are not easily divided. The division of social science into disciplines such as policy studies, political science, economics, sociology, and social geography create insularity. These artificial divisions are not natural to study complex system processes as a whole (Epstein & Axtel, 1996). Complexity can incorporate social, economic, spatial, and interacting environmental features of real-world social phenomena into models. The sheer power of computer simulation is breaking boundaries between disciplines, transforming social science into a computable, generative, and constructive science (Epstein & Axtel, 1996).

To capitalize on simulation capabilities, complexity can model descriptively or by rule-based criteria, or a combination of both. In descriptive modeling, the goal is to depict and describe actual, past, or future states of systems work from data-rich qualitative research. Rule-based modeling draws from equations, theories, principles, and assumptions. The goal is to envision and deduce possible present, future, or past states of a system. Effective complexity research includes features of both descriptive and rule-based modeling techniques for multi-level analysis. Additionally, complexity methodology can account for networks, non-linearity, self-organization, and the mixture of regularity and randomness that traditional research cannot (Sayama, 2010). With its flexible modeling techniques and use by a variety of sub-disciplines that can begin to model whole social systems, complexity science has the potential to push the frontiers of policy research.

Policymaking Considerations with Complexity Science

The ultimate goal is to take into account the unique nature of complex adaptive systems and incorporate its specialized criteria, mechanisms, and functions into effective policy. As a start, an action or external stimulus that impacts complex systems can be understood by the domino effect. Each system, sub-system, and component is impacted by a changing environment, and it responds by reorganizing into a totally new system. To change policy, something must happen. There must be a perturbation or change in the status quo by external stimuli or novelty. The change can occur in reactive form from random events or unexpected consequences and actions.However, it is critical to consider system resilience that enables and strengthens the system to absorb shocks from random events and unanticipated consequences of action. A change in policy is a proactive stimulus action that causes a new system state. If the change in the system causes an adaptation of improvement and strengthening, it evolves. If the change in the system causes an adaptation of deterioration, the system succumbs to entropy (Johnson, 2010).

Ideally, policy research strategies need to move dramatically beyond the practice of isolating systems and instead reinforce the natural processes of complexity. Policy makers need to consider incorporating constructs of a complex adaptive system's flexibility and diversity along with both positive and negative feedback mechanisms to enhance positive policy outcomes. Policy formation that recognizes the whole policy system should lead to implementation that causes action and, consequently, change.

Successful adaptation should result in an evolving system that is strengthened and becomes more sustainable and resilient. It is strategically imperative to ensure stronger interactions within sub-systems as well as between them, by capturing and exploiting existing system dynamics. Due to the non-linear and unpredictable nature of complex social systems, a large change could cause a small impact on policy outcomes.

In contrast, making small changes in a system can have significant impact if given the opportunity to go through stages of learning and feedback into eventual phase transition. Finally, it is critical to focus on system links that can generate a very large effect (Johnson, 2010).Complexity can provide invaluable information regarding which actions are preferable in guiding a complex policy system toward a desired course. Peat asserts that policymakers need to be context sensitive to information and act in ways that take into account changing system dynamics and be aware of all parts (Peat, 2013). Solving policy problems the traditional way can cause new and unintended problems in the system. Some systems can prove unyielding to change while others are highly sensitive to externalities. Attempting to control systems may result in unpredictable and unwanted outcomes. Peat suggests a very gentle steering of the whole system, coordinating parts in response to ever changing environmental conditions.

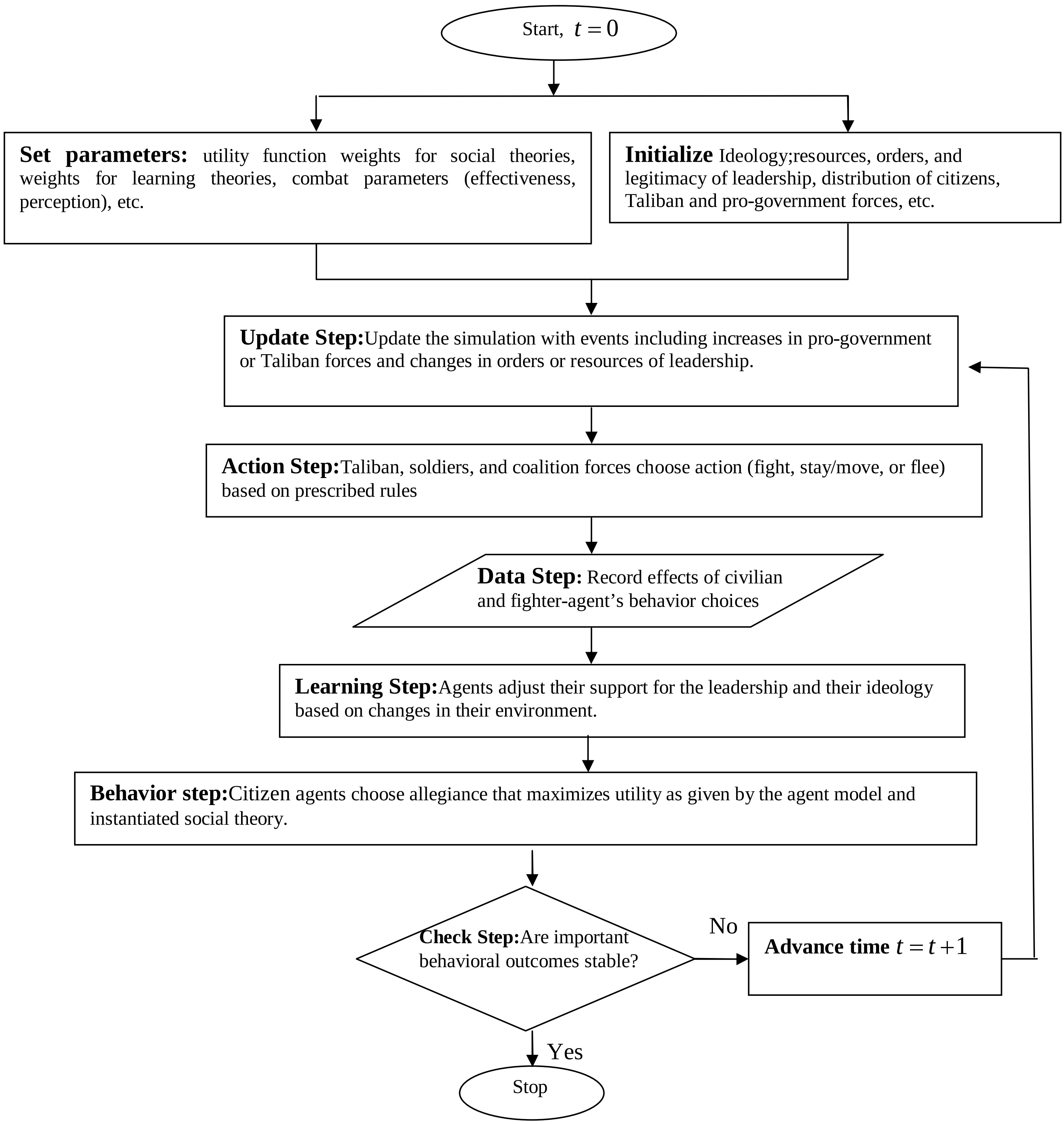
Furthermore, complex social systems endure fluctuations and perturbations that deviate from equilibrium. These fluctuations can add to a system's resiliency and robustness, which can keep it sustainable (Peat, 2013). The key to translating complexity mechanisms into useful policy research is discovering how parts of systems interact and give rise to predictable patterns. The next step is to observe the dynamic relationships of the whole and interdependent sub-systems. Social systems differ from physical systems in that people learn and adapt. Agents themselves can choose their level of connectedness, interdependence, adaptivity, and responsiveness. Researchers should focus their attention on evolutionary learning and dynamic connections in social systems to better understand macro system resiliency in the face of threats or challenges.

Sample Policy Example: Afghanistan Citizen Alliance

As an example of the kind of strategic complexity methodology we are advocating, we will describe a computer simulation model we developed on citizen allegiance in current Afghanistan (Whitmeyer et al. 2008).This model is a multi-agent system built on a Netlogo platform. A grid of 865 patches (cells) is superimposed on the political map of Afghanistan. The initial simulation set-up populates the environmental grid with three types of agents: citizen agents, Taliban fighters, and pro-government fighters, which come in two sub-types: coalition forces and the Afghan National Army.The principal dynamic process is that in each time-step iteration and in each patch, the simulation evaluates the possibility and level of conflict between Taliban and government forces. Conflict with significant outcomes and consequences could occur, resulting in citizen flight, or nothing may happen. Lastly in the process, citizens make a decision as to their allegiance. One form of feedback in the model demonstrates the specific allegiance of citizens, which affects both the likelihood and outcome of conflict. A time step is equivalent to three days. Figure 1 presents a summary flow chart of the simulation.

Parameters set by the user include initial or fixed values for attributes of agents, characteristics of regions, parameters governing the conflict process, regeneration rates for different kinds of agents, and the weights that determine the social science theories the simulation uses. Some elements of the model come from available data about Afghanistan found inLandScan Global (land use patterns), Afghan Information Management Service (district ethnic profiles), National Geographic (maps), and Gallup World Poll (population attitudes). These include the political map, the distribution of ethnicity, the typical ideology of ethnic groups (a parameter that varies on a continuum from pro-Taliban through neutral to pro-government), the distribution of the key agricultural product (opium), and the ideology of ethnic (regional) leaders, which informs the initial settings for the orders (to be pro-Taliban, neutral, or pro-government) of the leadership.

Figure 1. Conceptual Flow Chart of the Afghanistan Simulation

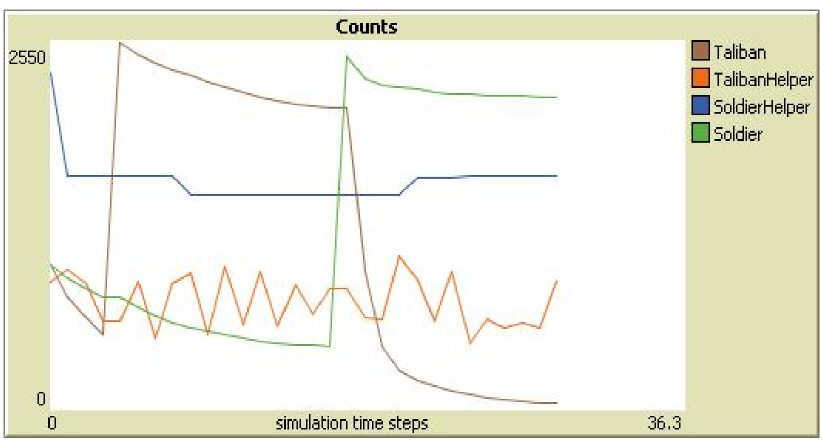


Given this is a model of the entire country, with possible movements of both soldiers and Taliban fighters throughout, as well as the spread of social influence, events in one region can have eventual repercussions elsewhere. The repercussions of the soldier and Taliban movements may be permanent or just temporary in the simulation. The model allows for changes in critical aspects of the empirical simulation to be made easily. For example, before running the model, adjustments can be made to model parameters, like the ideological leanings of an ethnic group and leadership characteristics of a specified ethnic group. While the model is running, the user can make changes, notably in leadership orders and resource allocation.

Also, the user can change parameters to represent regionally specific surges or decreases in agents of a given kind, such as fighters from either side or citizens. This allows the user to examine the effects of possible system perturbations. Variation in results occurs because the outcomes of conflict and the spread of influence are decided probabilistically. Lastly, so that the model does not dictate the social science theory used in the simulation, the model allows the user to choose between several alternative social theories of individual allegiance or to custom build a theory. These theories include different conceptions of how a citizen's behavioral choices and allegiance may be affected by those of other citizens. The model also allows the user to choose between different psychological theories of possible change in a citizen's ideology and in a citizen's perception of the legitimacy of the leadership.

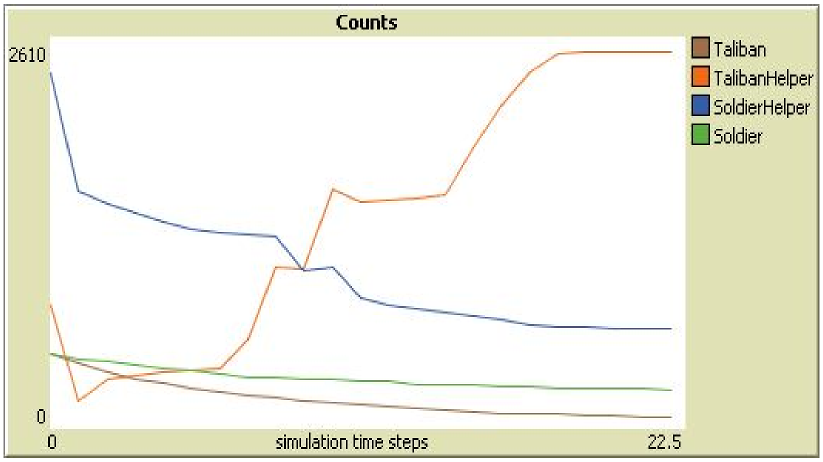
We describe briefly outcomes of the model under two different scenarios. The first demonstrates use of the model to examine effects of policy. The sequence of events (and the number of time steps allotted to them in the simulation) was as follows: 0. initialization (3 time steps); 1. a large influx of insurgents into a region (3 time steps); 2. a change in the regional leadership's orders from "support the government" to "remain neutral" (3 time steps); 3.a drop in the resources of the regional leadership (6 time steps); 4. a surge into the region of pro-government fighters (3 time steps); 5. a switch in the regional leadership's orders back from "remain neutral" to "support the government" (3 time steps); and 6. an increase in the resources of the regional leadership (6 time steps). Figure 2 displays the levels over time of Taliban helpers and soldier helpers, i.e., citizen allegiance, and of fighters. Levels of neutral citizens are not displayed. Note the effects of the counter-surge (event 4): while the levels of Taliban fighters sharply drop, there is little effect on citizen allegiance. The initial surge by the Taliban and changes in the regional leadership's orders (events 1 and 2) primarily have the effect of increasing the variability of support for the Taliban.

Figure 2. Citizen allegiance and fighter levels in surge and counter-surge scenario.



The second scenario is based on news reports of attempts by insurgents to gain influence in a region through co-opting the leadership. The key event was a switch in time step 6 of the leadership's orders from "remain neutral" to "support the insurgents." Figure 3 shows levels of citizen allegiance and fighters over time. Note that the effect on citizen allegiance, that is, on the levels of Taliban helpers and soldier helpers, is gradual, taking at least 15 time steps. The simulation also generates a spatial display (not shown), which in this scenario shows a small concentration of high allegiance to the insurgents immediately following the change in orders and, then a gradual spread of that allegiance until it covers the entire region for that ethnic group.

Figure 3. Citizen allegiance and fighter levels in co-option of leadership scenario.



Limitations of Complexity Science Methodology

Complexity methodology is by no means perfect, nor the answer to all policy research problems. However, if properly designed, implemented, verified, and validated, it can add significantly to policy research and be utilized in the real world likethe Afghanistan model. Yet no computational model will ever be fully verifiable and validated (Macal, 2005). Complexity simulations can be viewed as an innovative and illustrative way to approach policy research. As an additional research tool, they are intended to complement and enhance traditional research, not replace it(Achorn, 2004). Translating theories and qualitative data into reducible programming language can be challenging. Computers do not possess researchers' subtle, refined knowledge about human behavior that can skew intended research objectives. There is also the risk of developing a strong model, but designing computer code that does not accurately represent the model assumptions or the goals of the research (Macal, 2005).

Some systems can simply be too complex to model. Researchers cannot model everything. Researchers do not have perfect knowledge of complex systems, which also makes perfect modeling impossible. There is always the risk in any model of omitting parts, critical variables, interactions, assumptions, and mechanisms. Additionally, the inner workings of systems may not yet be revealed. Furthermore, complexity research applied to policy can result in no emergence and insignificant outcomes. Policy studies lags behind other disciplines, such as economics and sociology, in the acceptance and use of complexity methodology. However, there remains a great opportunity to refine and apply knowledge in complexity science to capture the nuances needed to further policy studies. Achorn (2004) states complexity tools are advantageous when there are numerous interrelated factors such as complex interactions between agents, heterogeneous populations, and actions whereby agents, learn and adapt. Finally, the goal should not be precise predictions, but insight into system patterns revealing tipping points or vulnerabilities. Simulations do not usually offer a high level of accuracy for specified event outcomes, but can still forecast the occurrence of novel events or emergence.

Perfect replications of complex social processes are not feasible. Still, complexity tools have the potential to help researchers move beyond the constraints of traditional policy research.

Conclusions

Epistemological researchers like Popper assert that all life is problem solving and "…we ought to try hard as we can to overthrow our solution rather than defend it" (Popper [1959] 2008, XIX). We concur and believe the research focus in policy studies should be more comprehensively directed to preventing and solving problems. More importantly, with the world becoming more complex, we should consider adjusting the focus of policy research to also account for interacting variables and interacting systems that impact research outcomes.Complexity science is certainly one additional approach to assist with this challenging task in the hopes of moving policy research forward where researchers solve problems instead of add to them. Complexity modeling simulations are just one technique to facilitate discovery and formalization so as to gain better understanding, insight, and prediction of some aspect of the social world (Gilbert & Troitzsch 2005).

Complexity science can provide major insights into interactions at the agent and system level to better understand connectivity, adaptation, and interdependent actions. Also, policy researchers can benefit from dynamic, process research that takes into account self-organization of social phenomena. The goal should be system improvement and how to avoid system deterioration, which is not how policy research is typically approached. Knowledge of critical connections and interactions can add to a base of research knowledge to create more optimal policy research and consequent outcomes.

We simply need to pay more attention to the impacts of complex systems' consequent causes and effects in order to direct more effective research and policymaking. In fact, applying complexity science to policy studies is a fertile and wide-open area for researchers to apply their expertise and unique perspectives. Further development and implementation of complexity research can add synergy and greater depth into both complexity science and policy studies. Creating the vision, developing scenarios, and exploring the possibilities with complexity opens up an exciting future for policy research. However, even if researchers uncover the mysteries of complex systems, they cannot make the serious mistake of thinking they can control complex systems by controlling interactions. The best they can hope for is to eventually learn how to harness complexity and be mindful…."an actor in a complex system controls almost nothing, but influences almost everything" (Page, 2009, p. 192).

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