Robustness, Adaptivity, and Resiliency Analysis
Steven Bankes

BAE Systems
4301 N. Fairfax Dr., St. 800
Arlington VA 22203
Steven.bankes@gmail.com

Abstract
In order to better understand the mechanisms that lead to resiliency in natural systems, to support decisions that lead to greater resiliency in systems we effect, and to create models that will utilized in highly resilient systems, methods for resiliency analysis will be required. Existing methods and technology for robustness analysis provide a foundation for a rigorous approach to resiliency analysis, but extensions are necessary to address the multiple time scales that must be modeled to understand highly adaptive systems. Further, if resiliency modeling is to be effective, it must be contextualized, requiring that the supporting software will need to mirror the systems being modeling by being pace layered and adaptive.

Resiliency and Robustness
Resiliency is the term that has achieved great popularity of late. In questions of ecosystem management, physical infrastructure, organizational dynamics, and individual psychology, resilience is a broadly sought goal. (Flynn, 2008; Sheffi, 2007) Community, regional, and national resilience is needed to contend with a growing range of threats. However, established means for rigorously analyzing choices in terms of their impact on resiliency do not exist, and there is not even a broad consensus on a definition for the term.

In contrast, “robustness” is a term that while multiply defined, has significant associated methods for analyzing both systems and decisions. (Bankes, 1993, 2002, 2005; Ben-Haim, 2006; Brooks et al, 1999; Groves and Lempert, 2007; Groves et al, 2008; Lempert, 2002; Lempert et al, 2003) There is clearly a relationship between resiliency and robustness, and it is tempting to define them synonymously. One might say perhaps that systems are resilient and decisions are robust, so that robustness analysis is all that one needs to address questions of resiliency. However, it is useful to differentially define these terms so as to reveal properties of resiliency that go beyond what has been regarded as robustness in previous studies. Robustness can be generally understood as the ability to withstand or survive external shocks; to be stable in spite of uncertainty. (Lempert et al, 2002, 2006; Lempert and Groves, 2010) So, for example, the designers of medieval castles might infer from the size of existing cannons how thick to build their walls in order to provide a level of robustness to shelling. Robust decision methods provide solutions that trade-off among different risks and multiple objectives to allow us to confront a list of known unknowns. (Bankes et al, 2002; Bankes and Lempert, 2004) And robustness analysis is increasingly becoming a well-established capability.

In contrast many definitions of resiliency involve some phrase such as recover from or bounce back from external shocks. Recovery implies a failure of robustness on a shorter time scale than that at which the system is judged to be resilient. In our medieval example, resiliency might take the form of multiple castle walls and a series of contingency plans including in extremis abandoning the castle altogether. Resiliency mechanisms provide adaptive capacity and fail soft augmentation to robustness and a means for dealing with unknown unknowns. Analytic methods focused on assessing resiliency would provide an improved understanding of the sources of resiliency in natural systems and a means to do a better job of seeking resiliency in our decisions, policies, and designs.

Robustness Analysis
The resource base of methodology and software for robustness analysis provides a solid foundation for establishing a practice of resiliency analysis. Constellations of computational experiments can be used to seek possible failure scenarios for any design or decision. (Bankes, 1993, 2002; Davis et al, 2007) They can reveal load bearing assumptions behind our reasoning, and assist in discovering decision options that promote resiliency and adaptive capacity. Robust decision methods:

- can produce actionable decisions in the face of uncertainty
- seek robust rather than optimal policies
facilitate developing adaptive plans and strategies by discovering warning conditions of failure scenarios that can be used to trigger adaptive mechanisms.

support mixed initiative planning with people-in-the-loop allowing us to combine machine and human insights.

identify strategies whose performance is largely insensitive to uncertainties

characterize which uncertainties are relevant to policy choices.

provide algorithms for inference that can combine approximate models with incomplete data resulting in better decisions than either model or data alone.

These attributes and techniques of robustness analysis will remain useful in trying to seek resilient options and decisions that lead to resiliency. And practical robustness analysis for resiliency studies is now increasingly possible. Parallel processing enables us to use large numbers of modeling experiments both because of the growing availability of multicore processors and because of the surge capabilities that cloud computing can provide. Advanced algorithms for reasoning about high dimensional spaces can provide efficiency in the way we use these hardware resources for exploratory modeling.

Multiscale Modeling For Resiliency Analysis

Mature resiliency analysis will require additional methods and technology beyond what is used for robustness. As resiliency inherently involves adaptive mechanisms, as resiliency analysis inherently must address phenomena at multiple time scales. Further, highly resilient systems will contain multiple adaptive mechanisms and be able to cope with a variety of shocks at different time scales. Consequently, resiliency analysis must be able to contend the multiplicity of time scales and so must augment the techniques of robustness analysis with explicit multiscale representations. This will mean both representing processes of multiple timescales and providing for multiscale challenge and option sets. Various literatures provide a starting point for thinking about this issue. The ecosystem resilience literature (Gunderson and Holling, 2002) explicitly considers in ecosystem contexts adaptive cycles operating in multiple time and spatial scales. They address questions of buffering versus cascade failure in terms of the phase relationships among such adaptive cycles. More generally Stewart Brand introduced the concept of pace layered systems, originally the context of architecture (Brand, 1994), but eventually generalized across a broad range of natural and social phenomena (Brand, 1999). Brand understands resiliency to require a layered architecture with very slow to change layers providing a framework on which faster layers operate, and the integration over faster dynamics driving change at slower pace layers. In order to extend demonstrated capabilities for robustness analysis to establish resiliency analysis, means for representing knowledge about dynamics at multiple temporal scales must be provided. This will require capability to compose models with very different representational structures in order to capture knowledge about dynamics at different time scales and to create methods for their interaction. This interaction needs to allow the integration of changes in fast paced layers driving the formation of structure at slower layers and for slow change layers to provide the context for dynamics which occurs in the faster time scale models. Such a multiscale modeling capability would allow, for example, addressing questions where knowledge about individual cognition can be combined with dynamics of social networks and with community level processes including cultural change. By addressing problems at multiple scales we could consider portfolios of policies which span the same range of time scales including, for example, quick interventions such as outreach to individuals with slower approaches such as influencing thought leaders in social networks and bridge building and educational projects to affect community level processes.

Resiliency Modeling Infrastructure

These requirements of resiliency analysis have significant implications for modeling practice. The techniques of robustness analysis can be still used to assess resiliency and design resilient options but additional issues must be addressed. Multiple timescales imply multiple attributes in any scenario will need to be considered. This means analysis cannot be based on optimizing a single valued function but that multiattribute techniques must be inherent in any resiliency analysis. In particular both long-term and short-term performance issues must be addressed. Testing for resiliency to surprise requires a need for the representing a broad diversity of potential challenges for stress testing purposes. This in turn implies a need for a wide diversity of model types in order to be able to represent diverse challenge dynamics. There will need to be particular attention to issues of temporal scale, multiscale modeling, and reasoning across models that operate at different scales. There must be a pace layered representation of both challenges and policy options.
Finally, the use of multiple modeling formats within an analysis means that techniques for using models jointly and for model composition will be important for resiliency analysis. And model composition itself will need to be adaptive and contingent. Static model wiring will not capture adaptive mechanisms that would alter intra-model linkage. This means that the software system that supports resiliency analysis must itself be adaptive and pace layered.

While this latter requirement significantly changes the way we create and exploit models it is important to note that it is not without precedent and will not require a discontinuous innovation in software engineering. The metropolis model of Kazman and Chen (2009) embodies the realization that software supporting both social networking and open source development is itself pace layered. These software development efforts are characterized by a kernel that is slow to be modified and for which only a small number of developers have access. This kernel is surrounded by additional software layers each with increasingly fast rates of change and increasingly large numbers of people involved. At the surface layer of social networking systems, the general public provides much of the content. Resilience analysis will require modeling systems that adopt these same principles, especially if it is intended that models resulting from the analysis be deployed as a component of a highly resilient system.

Modeling systems that support resilience analysis and have as their core features this capability for adaptive model composition can provide a means for addressing classes of problems that have been beyond our reach. In particular, the so-called wicked problems (Rittel and Webber, 1973) which require that problem framing be possible at the end of the development process rather the beginning can potentially be addressed by modeling systems with a capability to adapt after deployment. By supporting problem solving processes that allow iterative, decentralized, and continuous problem framing, we can continue spiral system development methods through and after deployment of software systems (Nardi and O’Day, 1999).

**Resiliency Modeling Methodology**

All of the foregoing implies that modern analytic practice must move beyond academic reductionism (Richardson, 2003). Ivory tower modeling approaches where the modeler stands outside the system of interest can remain useful for theory development. But, greater contribution to social outcomes will require that modeling be contextualized. In order to contend with nonstationary problems, and to transition complexity modeling from science to engineering, models must be deployed as a component of the solution.

Computational modeling makes a big contribution in providing a basis for representing the interaction of multiple interacting systems and an accounting for the true uncertainty attending our knowledge about causal relationships. However, the incorporation of complexity concepts in models that are then used in a reductionist fashion will not be adequate to provide for resiliency. Developing models that incorporate complexity concepts but then using them for prediction and forecasting simply adds non-linear modeling representations to fundamentally reductionist practice. In order to fully bring the insights of complexity science to policy and systems engineering, they must be applied not only to the construction of models but to their use. Institutions and decision makers are part of the systems they manage. In order to promote resiliency, the complete socio-technical system must be considered, including models of the system, the policy makers, and their decision processes.

In order to cope with highly complex and deeply uncertain systems it is going to be necessary to build models as they are to be used. Frequently, the system under study may change between model development and exploitation. Consequently, for complex problems, what is needed is not a single fixed and validated model but “just in time” support for modeling. For modeling to have a useful role as a component of a complex system, new modeling techniques and methods are needed. These may perhaps be thought of as “extreme modeling”, analogous to extreme programming. Modeling techniques akin to programming innovations devised to support Web 2.0 applications (O’Reilly, 2005) are needed that can provide the agility needed to contend with volatile environments, emergent requirements, and continuous model development.

At present, static closed models are used to represent open and evolving systems. Methods for creating open and adaptive model based infrastructure are needed to provide resilient solutions for these problems. Such open representations will presumably consist of a small, highly conserved kernel, and a much larger and more rapidly adapting periphery, just as do existing open source software projects and crowd sourcing based web applications (Kazman and Chen, 2009). Depending on the application, rates of change in the periphery will vary as well, resulting in the pace layering seen in many engineered and natural systems (Brand, 1999; Gunderson and Holling, 2002).

In this way, the process of modeling complex systems must evolve to more closely resemble the systems with which it contends. Just as the phenomena of interest are pace layered and emergent, so modeling itself must produce models composed from components that adapt to changes in their environment with varying paces of change. The challenges of doing this are significant. But the opportunity is for complexity modeling to become ubiquitous. Rather than a specialized activity that sits...
outside most of human life and economic activity, computational modeling can become a major means by which humans communicate with their technology. The practice of extreme modeling, which at this moment exists only in prospect, will allow us to cross the chasm between model creation and model use which has consigned computational science to a peripheral role up to now. The role of the computational scientist in this vision would not be the creation of final models but rather the creation of modeling infrastructure. That infrastructure would capture knowledge but also provide means of adaptation. Many capabilities may prove useful in establishing this approach, including improved means of representing and reasoning with structural model uncertainty, the ability to create models from composeable parts, and mixed initiative modeling where model snippets, human judgment, and data can all be used in the creation of model instances.

Deep Validation
A challenging aspect of the proposed approach to developing resiliency-centric software is that of maintaining modeling rigor, often described as the problem of model validation. Validation as typically understood is a testing stage that occurs between model development and use, performing the role of acceptance testing. This classical understanding of model validation is thus integral to a linear waterfall process for model development, and not suitable for the spiral processes advocated here. An alternative approach to assuring modeling rigor and reliability is that of “deep validation”. In “deep validation” the term “deep” is analogous to that in “deep time” (Brand, 1999) and “deep uncertainty” (Bankes, 2002, 2005).

An aspect of deep uncertainty that has not been addressed by current approaches to model validation is the nonstationarity of human systems. For many applications the world is not a static entity that can be described for all time by a finite list of initial parameters and boundary conditions. Rather, for many problems the world is in flux and conditions that were constant for all testing data can change in the future. Static assessment criteria, appropriate for physical models where the laws of physics and design of a device can be presumed constant, can among other problems, create a false sense of security when used with models developed for resiliency analysis. In particular, when modeling affairs involving human beings the underlying system can itself undergo disruptive transformation. New technologies, new political movements, new religious movements, and new fads can emerge unexpectedly and change the underlying system to behave differently than it did during a static stage of validation testing.

When the environment in which the model will eventually be employed can change in potentially unpredictable ways, a single "shallow" testing phase to determine if the model is correct will not be adequate. Instead, "deep" validation strategies are needed that span model construction, revision, adoption, and deployment. Validation must establish, among other things, the environment (including forms of continuing automated assessment) necessary to protect users from creeping or sudden validation loss.

Deep Validation is a systemic approach to assuring credible use of computer models in spite of potential changes to the system of interest. It requires iterative testing of the model in a fashion aligned with its eventual use.

Deep validation thus requires a model exploitation environment that incorporates meta-data for models and supports processes for assessing models and populating model meta-data as a consequence, and for utilizing this meta-data to support model utilization by users.

Key aspects of deep validation are:
- Testing models as they are to be used. While models can serve as vehicles to resolve theoretical issues, it is the utility of models that must be assessed both in model validation and in selecting models for particular applications. Validation is always relative to an intended use (Dept. of the Army, 1993; Dept. of the Navy, 2004; DoD, 2007). Testing to assess a model’s ability to track or forecast events can be highly relevant. However, in deciding on appropriateness of a model for a particular application, the model must be treated as an artifact that must reliably perform a function, not a statement that is either true or false.
- Assessment and testing are conducted throughout a model’s lifecycle. Assessment can commence at the stage when a model is first specified and designed. Useful testing can be done during development, including testing of model sub-components. Testing of model behavior at the end of model development is crucial for acceptance and transition to applied use. And, due to the possibility that the deployed environment will come to differ in important ways from that assumed during development, models must be supported by infrastructure that allows their performance in deployed settings to be continuously evaluated. This includes both means of model adaptation and mechanisms to alert users should unforeseen changes in the environment cause model performance to degrade.
- The determination of the assumptions and constraints that must be satisfied for reliable model use is an essential product of all testing and assessment. While other model properties (meta-data) may be usefully gathered, assumptions and constraints provide the basis for both selecting models and for monitoring their performance. Assumptions and constraints also provide a conceptual description of core meta-data that can be accumulated and revised throughout a model’s life cycle.
The deep validation concept is potentially consistent with any and all existing approaches to validation and testing, including concepts of internal and external validity, testing of predictive accuracy against historical cases, face validation by subject matter experts, and social Turing tests. However, deep validation is more systemic than single stages of validation testing, usefully can combine multiple different testing protocols, and in being more systemic has the potential to be much more rigorous and comprehensive than any currently used approach for model validation and testing.

The required software tooling to support deep validation includes data structures that will capture all relevant model meta-data, a series of assessment processes appropriate to the various stages of a model’s life cycle that will populate this meta-data, and application specific model selection processes that will utilize this meta-data to ensure appropriate model use.

**Challenge and Opportunity**

One of the great challenges before our technological culture is creating systems and institutions that are highly resilient in the face of complexity and deep uncertainty. To play its role, computational modeling must be able to adapt to changes both frequent and rare, and be able to contend with future situations that cannot now be anticipated. In reaching that goal, computational modeling can play a key role in making society resilient to future surprises.

Approaches that can incorporate knowledge from multiple sources including the knowledge which resides with final users can provide the means to address problems for which other techniques are not applicable. This will require increased attention to the design of software environments external to models which provide for model exploitation and ensure the delivery of value. A proof of principle as provided by the design of the Computer-Assisted Reasoning system (CARs) which contained a library of derivation operators that enabled the creation of model encapsulations driven by user reasoning goals (Bankes et al, 2002; Bankes and Lempert, 2004). These operators could be applied recursively, allowing arbitrarily complex platforms of computational experiments to be derived from a collection of atomic model pieces.

The prospect of resiliency analysis presents both challenges and opportunities. The practice of computational modeling and analysis practice needs to be extended to provide for multiscale modeling of dynamics, choice spaces, challenge sets and metrics. Multiscale and adaptive model composition needs to be supported. Once these challenges are met, resilience analysis can provide a broad range of new capabilities. It will be possible to evaluate the resiliency of societies, communities, and populations at risk, devise policies that promote economic development that is resilient to global shocks, design resilient infrastructures, and harmonize choices and policies across agencies and institutions. Resiliency analysis can provide an important antidote for current tendencies to focus on short term outcomes, which can be seen to often create enormous vulnerabilities in the long term.

**References**


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