

# Tools and techniques for developing policies for complex and uncertain systems

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**Agent-based models (ABM) are examples of complex adaptive systems, which can be characterized as those systems for which no model less complex than the system itself can accurately predict in detail how the system will behave at future times. Consequently, the standard tools of policy analysis, based as they are on devising policies that perform well on some best estimate model of the system, cannot be reliably used for ABM. This paper argues that policy analysis by using ABM requires an alternative approach to decision theory. The general characteristics of such an approach are described, and examples are provided of its application to policy analysis.**

## Introduction: The Need for New Tools

Quantitative policy analysis depends on a portfolio of tools that have been drawn from a variety of disciplines, including game theory, economics, statistical decision theory, and operations research. These tools are rigorous and sophisticated and have proven their value on a host of policy problems spanning several decades of research. To date, however, there are few good examples of the classical policy analysis tools being successfully used for a complete policy analysis of a problem where complexity and adaptation are central. Indeed, there are a sufficient number of examples of misleading analyses resulting from the naive application of these approaches to complex systems and in particular to analyses based on agent-based models (ABM) to suggest that there may be something fundamentally different about ABM that requires new tools.

This paper argues that the central feature of the classical tools that leads to difficulty is the identification of a single “best” model of the system of interest, followed by the use of that model to develop a policy that is “best” in the context of that model. Typically, the best policy is one that optimizes some cost or utility function for that model. Whereas this metatechnique is so ubiquitous that it may seem unavoidable, its justification is difficult when applied to complex systems. Any system whose behavior is well captured by some model cannot be complex, under most definitions of complexity. This concept is best seen by realizing that complex systems have perpetual novelty among their important attributes. Possession of an accurate model insures no surprises, and hence, no complexity. Because the usefulness of ABM to social science lies in ABM’s capacity to model the complexity of social systems, this general problem applies directly to the use of agent-based models.

Whereas there may be problems for which ABMs can be devised that do accurately predict system behavior, most agent based models of social systems will not have that property. For those problems for which no model can accurately predict the details of system behavior, approaches to policy analysis based on using some model to forecast system behavior will be inappropriate. For such problems, it will still be important to craft models that best use available information. But, no matter how well a model is crafted for such a problem, treating it as a forecast engine will lead to faulty reasoning. Policies that are optimal for some best estimate model may underperform very

badly in some regimes of behavior of the actual system not captured by the model. That is to say, optimal policies for best estimate models may not be robust across the range of possible behaviors of the complex adaptive social system they represent. More subtly, for complex adaptive systems, single models will frequently fail to exploit important knowledge that is available that could be used to help craft good policies. This very important fact is a consequence of yet another aspect of complex adaptive systems, known as “deep uncertainty.”

## Deep Uncertainty

Divergence between the detailed behavior of systems and the predictions of best estimate models is not unique to complex adaptive systems. This difference is known elsewhere as “uncertainty,” and is addressed by using the tools of probability, statistics, and statistical decision theory. If the knowledge and information that need to be represented can be captured by probability distributions, then the tools of statistical modeling and analysis are adequate to meet that challenge posed by complex systems, and there is no need for new concepts or new tools.

There are phenomena that are prosaically described as uncertain that are not well modeled by the tools of probability and statistics. Although controversial, this pragmatic reality has been recognized for some time (1, 2). The term I use to describe such phenomena is “deep uncertainty.”<sup>†</sup> The view of most statisticians is that no such thing as deep uncertainty exists. Decades of practical experience suggests otherwise.

Deep uncertainty is important not because some yet to be discovered theorem invalidates or extends probability and statistics in some fundamental way. Instead, deep uncertainty is the result of pragmatic limitations in our ability to use the representational formalisms of statistical decision theory to express all that we know about complex adaptive systems and their associated policy problems. The familiar tools are adequate for complicated systems that are relatively predictable (i.e., for computer-assisted design) or are uncertain but relatively simple (as in the relatively low dimensionality of most statistical models). But there are huge pragmatic barriers in actually applying these formalisms to problems that combine complexity with uncertainty (especially that very nonlinear source of uncertainty created by interacting adaptive agents). It is for these problems—those related to complex adaptive systems—that new tools are most needed.

This paper results from the Arthur M. Sackler Colloquium of the National Academy of Sciences, “Adaptive Agents, Intelligence, and Emergent Human Organization: Capturing Complexity through Agent-Based Modeling,” held October 4–6, 2001, at the Arnold and Mabel Beckman Center of the National Academies of Science and Engineering in Irvine, CA. Abbreviation: ABM, agent-based model.

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<sup>†</sup>The first use of the term “Deep Uncertainty” that I am aware of was by Nobel Prize winner Kenneth Arrow, in a talk delivered at the Pew Center Workshop on the Economics and Integrated Assessment of Climate Change, July 1999.

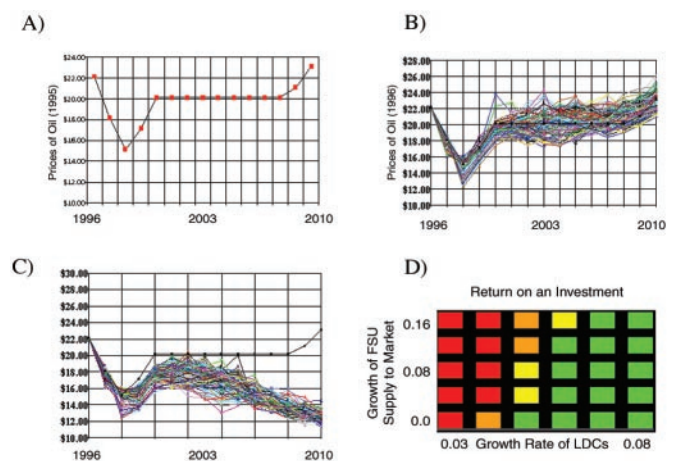
There are several reasons that the tools of probability and statistics that can in principle represent all knowledge about any problem do not suffice for many real problems. These reasons can be grouped into two main categories. First, the representations of probability and statistics often provide a poor *ontology* for capturing our knowledge about complex and adaptive systems, requiring that different representations be used if we are to use all our knowledge. This ontological deficiency is especially obvious for ABM, where dynamic agent generation and heterogeneity make representing the ensemble of possible agent model states through joint probability distributions especially challenging.

A second challenge to the use of the classical methods of statistical uncertainty analysis is that the assumptions that motivate the representational choices of probability and statistics are in conflict with the *pragmatics* of many policy contexts. Rather than a single monolithic decision maker, with coherent values and an explicitly describable state of knowledge, policy problems often present communities of stake holders, with values that are incommensurate and group knowledge that is very difficult to elicit and capture in a single probabilistic structure. These pragmatic challenges frequently require that something in addition to probabilistic approaches be used.

Fortunately, just as computational methods such as ABM make the problems of uncertainty analysis more vexing, innovations based on computational modeling provide an alternative to the available mathematical tools for meeting this challenge (3). In the remainder of this paper I will present several of the innovations that I believe are most fundamental and important. I have little doubt that a much longer list will be developed in the coming decade.

### Reasoning with Ensembles

Best estimate models are constructed by using available knowledge about the system of interest. When such a model does not predict the behavior of a system, it is often true that there is additional information available about the system that was not used in constructing the model. Often, more information can be captured in an ensemble of alternative plausible models than can be captured by any individual model. Indeed, probability distributions are a representation of just such an ensemble. But, the restrictions that are imposed by the mathematical formalisms of probability theory can in computational modeling be avoided by a combination of explicit enumeration of finite lists of alternative options and inductive reasoning about the properties of infinite ensembles represented with generative techniques. Computational tools enabling facile manipulation of ensembles of models provide an important approach to dealing with the ontology of deep uncertainty. Unexpectedly (by me at least), they also have provided an important foundation for addressing the pragmatics of deep uncertainty as well. This computational approach, referred to in some literatures as exploratory modeling or exploratory analysis (3), allows human analysts and decision makers to be interactively involved in selecting among alternative options during the course of an analysis. Mathematical frameworks like that of statistical decision theory require all knowledge to be acquired before the analysis can begin, which translates into a major barrier to using the qualitative and tacit knowledge held by humans and their organizations. Exploratory modeling allows such knowledge to emerge and be used throughout the course of an iterative analytic process. Consequently, it can provide a bridge for moving from deductive analysis of closed systems, to interactive analytic support for inductive reasoning about open systems where the contextual pragmatic knowledge possessed by users can be integrated with quantitative data residing in the computer (see ref. 3 and [www.evolving-logic.com](http://www.evolving-logic.com)).



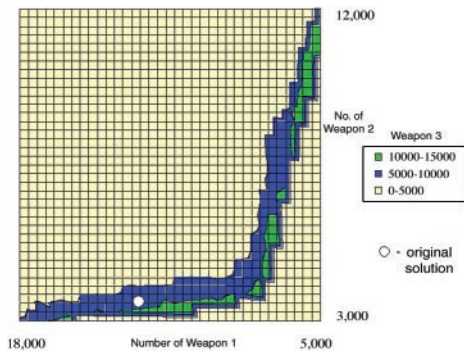
**Fig. 1.** Different uses for a model of oil prices. (A) Using the model as a prediction engine provides little benefit. (B) A Monte Carlo analysis provides partial indication of degree of uncertainties. (C) Exploration over structural uncertainties reveals there is additional real world uncertainty not captured in the uncertainty analysis. (D) A policy region analysis can be illuminating, even when uncertainties make forecasts unreliable.

Technology for manipulating ensembles can be applied to representing ensembles of alternative models, and also to ensembles of plausible futures, and for ensembles of candidate policies. This technology is used for all of the following techniques.

### Policy Landscapes

Policy analysis of complex systems will be challenging or impossible if agent-based models are used as closed systems to produce point forecasts, expressed either as a single vector of outputs, or a probability distribution over such vectors. For complex adaptive systems, especially those that are open, no such modeling exercise can be viewed as final and definitive. Instead, any calculation, including those that integrate over probabilistic representations, must be subjected to robustness testing. That is to say, the impact on policy conclusions of alternative modeling choices must be examined. The goal is to discover a policy recommendation that holds for all plausible models of the problem, or which can be demonstrated to be superior to all other options across this range of plausible models. Frequently, and especially in the face of deep uncertainty, alternative assumptions can lead to different outcomes. Model results can quickly provoke proposed changes to model architecture that might lead to different policy recommendations. Rather than hide from this common situation, we can exploit intermediate model outcomes to deepen our knowledge of the problem and exploit the not yet used tacit knowledge of human experts. Graphical depictions of the pattern of outcomes across a range of alternative assumptions can provide a significant improvement over point predictions, even those with accompanying sensitivity analysis.

Fig. 1 motivates the use of this technique. This example is based on a model developed by a major oil company to forecast the price of oil. The model used contained a great deal of class knowledge that could be useful in making a variety of important decisions, such as whether the company should invest in the construction of a new refinery. However, when the model is used as a prediction engine, very little benefit is derived, as Fig. 1A demonstrates. A single best estimate price path provides little help in making any decision, because both the model builder and the consumers of the analysis know that this “prediction” is nearly certain not to be correct. Indeed, this best estimate, made



**Fig. 2.** A level set of satisfactory policies provides significantly more utility than information about the single “optimal” policy in this model of military combat, labeled here “original solution.”

in 1997, can now be seen retrospectively to have matched the actual price of oil very poorly indeed. The situation would be no different if we did a retrospective of the predictions of combat models of the casualties in the Gulf War, or macroeconomic model prediction of gross domestic product (GDP) for more than a few quarters into the future.

Fig. 1B presents what typically results from a Monte Carlo analysis, where probabilities are introduced to represent uncertainty and stochasticity. The range of plausible behavior provided by this graphic is a clear improvement over point prediction. However, this output still greatly underestimates the actual uncertainty facing the decision maker. This Monte Carlo simulation was done by varying those quantitative parameters for which probabilities could be easily estimated. For this problem (and others characterized by deep uncertainty) there are a host of structural or model uncertainties that are much more difficult to suggest good probability distributions for. Similarly, a variety of exogenous events could occur that would greatly affect the price of oil. Fig. 1C shows the result of one such excursion, where oil fields in former Soviet republics are assumed to come on the market more rapidly than was estimated in the baseline model. This is but an example of such a plausible alternative future. Others include a collapse in third world economies, and along with it the demand for oil, or a revolution in the Middle East that interrupted the production of oil.

All of these issues could, in theory, be handled by the probabilistic machinery of statistical modeling. However, the pragmatics of very complex real world systems is such that this method is essentially never done for real problems and real models. Instead, invariably the rhetoric of prediction (including probabilistic prediction) gets used, even when these predictions are suspect. Curves such as Fig. 1C are seldom produced, and the set of all such possible graphs is seldom considered, because the conclusion is readily drawn that we have little idea what the price of oil will be in 10 years. And without some sort of forecast, what use is a model of the price of oil? For that matter, what use is any model of a complex system whose predictions do not come true?

One simple answer is provided in Fig. 1D. Whereas a wide range of oil prices is possible, there is structure in the ensemble of plausible scenarios that generates this price range. And that structure, properly organized and graphically portrayed, can support the reasoning of the analyst or decision maker. In Fig. 1D is portrayed the rate of return of a notional investment whose performance is tied to the price of oil. This performance is color coded based on the natural nonlinearity of the corporate standard hurdle rate for viewing investments as attractive. This two-dimensional picture is a slice through a multidimensional landscape of possible excursions. The position and orientation of

the slice can be interactively controlled by the user, allowing the pattern of outcomes across a multidimensional scenario space to be examined.

### Level Sets of Satisfactory Solutions

Just as no single model can capture all of the knowledge that may be available for a complex adaptive system, no single policy recommendation, calculated to optimize a cost function on that model does either. And for policy analysis, a policy recommendation is not just a mechanical control, it conveys information that is then used by human beings.

An alternative to using agent-based models to recommend single policies is to provide decision makers with ensembles of policy options all of which perform satisfactorily. Such an ensemble can be a level set of policies that perform better than some threshold on a cost function. This approach can provide much better support for satisfying decision making strategies that are commonly used by real decision makers (4). An example is shown in Fig. 2. This figure is drawn from work done for the U.S. Air Force on weapons procurement (5). The task is to select a portfolio of deep attack weapons to be procured in preparation for some future conflict. What is often done is to use a high resolution simulation of such a conflict, and to search for the optimum portfolio of weapons to achieve combat goals in that simulation. In this example, the model CTEM was used, and the resulting optimum portfolio was a mix of three weapon systems, shown as the white circle at the bottom of the diagram. This single point provides poor support for humans who have knowledge that the model does not, to combine their insight and contextual knowledge with the outputs of the model. Much better information is provided by the level set of weapons mixes that comes within 5% of the performance of that optimal portfolio. The resulting boomerang shaped level set clearly shows the complementarity of the two weapons types whose numbers make up the axes of the graph.

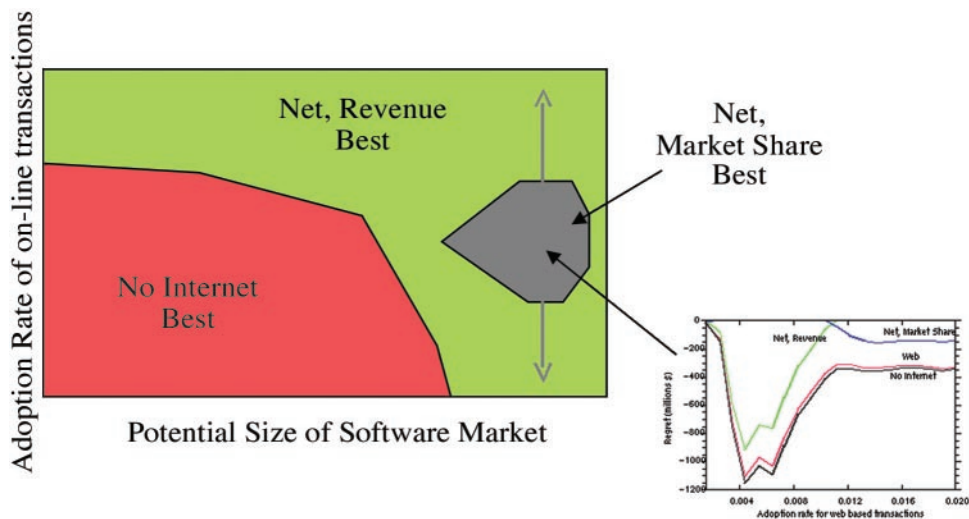
Contrast the level set of satisfactory policies to the “take it or leave it” single optimal policy recommendation. Note that the level set provides experts with much more information about the pattern of model performance as policies vary. Using this format for the output of an analysis provides decision makers an opportunity to exploit the qualitative contextual knowledge they possess that is not incorporated into the model in picking a final policy option out of the ensemble of alternatives.

### Robust Strategies

A level set provides much more information than does a single optimal policy. Combining this idea with that of policy landscapes, the computer can be used to discover policies that are robust across multiple scenarios or alternative models, and to identify and graphically depict sets of policies with satisfactory robustness.

One way to do this process is to intersect a finite number of level sets created with different models or different scenarios or assumptions. One can also calculate a robustness metric, such as regret (1), and then create landscapes and level sets showing what policy options are satisfactorily robust under what assumptions.

An example of such a diagram is shown in Fig. 3. This figure is drawn from an unpublished study of e-commerce strategy for a company modeled loosely on the Intuit Corporation. In Fig. 3, the performance of four alternative product strategies is compared across varying assumptions about potential size and growth rates in the markets for shrink wrapped software and on-line transactions. The larger figure shows the identity of the best strategy across this landscape of possible cases. (One of the four strategies turns out to never be the best strategy.) Various robustness criteria (for example, minimizing the maximum regret) can be used to recommend one of the candidate strategies.



**Fig. 3.** Performance of four alternative product strategies compared by using a model of an electronic commerce rate market. This figure demonstrates how an exploration of patterns of outcome across possible actions can provide more information than simply optimizing robustness (through, for example, minimizing the maximum regret). In this case, for example, examination of this diagram could stimulate investigation of new options for adaptively combining the two product strategies, "Net, Revenue Best" and "Net, Market Share Best."

For this example, the strategy of network deployment, pricing for early revenue (shown here in green) is typically recommended by such criteria, for reasons that can be discerned by examining the *Inset* line graph. However, as the larger landscape diagram reveals, there is a region in scenario space where the alternative strategy of net deployment and pricing for market share is superior. By examining visualizations such as this one, users can be prompted to enlarge the set of options by constructing composites that combine the best elements of component strategies that are good over limited ranges of scenarios. One option for doing this method is to construct adaptive strategies that change in response to improved information that will become available in the future. Because pricing strategies can be selected after product designs are fixed, such adaptive strategies are a possible candidate for this example.

### Adaptive Strategies

Successful policies for complex, adaptive systems will typically need to be adaptive themselves. But, relying on optimization to craft policies based on the forecasts of single models results in static policies that always make the correct move for that best estimate model. To test adaptive policies, a challenge set of possible future situations is needed, and the ensembles of alternative models being used for all of the previous techniques are perfect for this. Similarly, adaptive policies need to be evaluated on their robustness properties, not on their performance on any single case. So, all of the previous tools and

techniques serve to lay a foundation on which adaptive policies can be crafted. Further, the computer can be used to find important scenarios by searching through such ensembles, in particular to find cases that break a proposed policy. Such worst cases can stimulate users to modify the range of possible policies to allow for combinations that hedge against these possibilities. This strategy can allow users to iterate with the computer to gradually evolve policy schemas that have particular policy instances with desirable properties.

This approach has been successfully used in several studies to make concrete policy recommendations for deeply uncertain problems by using very nonlinear simulations including agent-based (6–9).

### Conclusions

Whereas complex adaptive systems and agent-based models of them originally seemed to pose a problem for policy analysis, they may also present an opportunity. The failure of computerized decision support systems to provide significant help for most problems is striking when contrasted with the impact of computer technology in other spheres. Looking back, we can now see that most policy problems involve complex and adaptive systems, and that for those problems the classical approaches of predictive modeling and optimization that have been used in decision support software are not appropriate. The next stage in the development of complexity science could well include a reformulation of decision theory and the emergence of the first really useful computer-assisted reasoning for policy analysis.

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