Deep Uncertainty

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Without Abstract

Uncertainty In Model-Based Decision Support

The notion of uncertainty has taken different meanings and emphases in various fields, including the physical sciences, engineering, statistics, economics, finance, insurance, philosophy, and psychology. Analyzing the notion in each discipline can provide a specific historical context and scope in terms of problem domain, relevant theory, methods, and tools for handling uncertainty. Such analyses are given by Agusdinata (2008), van Asselt (2000), Morgan and Henrion (1990), andSmithson (1989).

In general, uncertainty can be defined as *limited knowledge*about future, past, or current events. With respect to policymaking, the extent of uncertainty clearly involves subjectivity, since it is related to the satisfaction with existing knowledge, which is colored by the underlying values and perspectives of the policymakerand the various actors involved in the policymaking process, and the decision options available to them.

Shannon (1948) formalized the relationship between the uncertainty about an event and information in his 1948 paper "A Mathematical Theory of Communication." He defined a concept he called *entropy* as a measure of the average information content associated with a random outcome. Roughly speaking, the concept of entropy in information theory describes how much information there is in a signal or event and relates this to the degree of uncertainty about a given event having some probability distribution.

Uncertainty is not simply the absence of knowledge. Funtowicz and Ravetz (1990) describe uncertainty as a situation of inadequate information, which can be of three sorts:inexactness, unreliability, and border with ignorance. However, uncertainty can prevail in situations in which ample information is available (Van Asselt and Rotmans, 2002). Furthermore, new information can

either decrease or increase uncertainty. New knowledge on complex processes may reveal the presence of uncertainties that were previously unknown or were understated. In this way, more knowledge illuminates that one's understanding is more limited or that the processes are more complex than previously thought (van der Sluijs, 1997).

Uncertainty as inadequacy of knowledge has a very long history, dating back to philosophical questions debated among the ancient Greeks about the certainty of knowledge, and perhaps even further. Its modern history begins around 1921, when Knight made a distinction between risk and uncertainty (Knight, 1921) . According to Knight, risk denotes the calculable and thus controllable part of all that is unknowable. The remainder is the uncertain −incalculable and uncontrollable. Luce and Raiffa (1957) adopted these labels to distinguish between decisionmaking under risk and decisionmaking under uncertainty. Similarly, Quade (1989) makes a distinction between "stochastic" uncertainty and "real" uncertainty. According to Quade, stochastic uncertainty includes frequency-based probabilities and subjective (Bayesian) probabilities. Real uncertainty covers the future state of the world and the uncertainty resulting from the strategic behavior of other actors. Often, attempts to express the degree of certainty and uncertainty have been linked to whether or not to use probabilities, as exemplified by Morgan and Henrion (1990), who make a distinction between uncertainties that can be treated through probabilities and uncertainties that cannot. Uncertainties that cannot be treated probabilistically include model structure uncertainty and situations in which experts cannot agree upon the probabilities. These are the more important and hardest to handle types of uncertainties (Morgan, 2003). As Quade (1989, p. 160) wrote: "Stochastic uncertainties are therefore among the least of our worries; their effects are swamped by uncertainties about the state of the world and human factors for which we know absolutely nothing about probability distributions and little more about the possible outcomes." These kinds of uncertainties are now referred to as deep uncertainty (Lempert et al., 2003), or severe uncertainty (Ben-Haim, 2006).

The Levels of Uncertainty

Walker, et al. (2003), define uncertainty to be "*any departure from the (unachievable) ideal of complete determinism*." Or, in mathematical terms:

Let Y be some event. If Probability(Y) ≠ 0 or 1, then the event Y is uncertain.

For purposes of determining ways of dealing with uncertainty in developing public policies or business strategies, one can distinguish two extreme levels of uncertainty (complete certainty and total ignorance) and five intermediate levels (e.g. Courtney, 2001; Walker et al., 2003; Makridakis et al., 2009; Kwakkel et al., 2010d). In Figure 1, the five levels are defined with respect to the knowledge

assumed about the various aspects of a policy problem: (a) the future world, (b) the model of the relevant system for that future world, (c) the outcomes from the system, and (d) the weights that the various stakeholders will put on the outcomes. The levels of uncertainty are briefly discussed below.

Complete certainty is the situation in which everything is known precisely. It is not attainable, but acts as a limiting characteristic at one end of the spectrum.

Level 1 uncertainty represents the situation in which one admits that one is not absolutely certain, but one is not willing or able to measure the degree of uncertainty in any explicit way (Hillier and Lieberman, 2001, p. 43). Level 1 uncertainty is often treated through a simple sensitivity analysis of model parameters, where the impacts of small perturbations of model input parameters on the outcomes of a model are assessed.

Level 2 uncertainty is any uncertainty that can be described adequately in statistical terms. In the case of uncertainty about the future, Level 2 uncertainty is often captured in the form of either a (single) forecast (usually trend based) with a confidence interval or multiple forecasts ('scenarios') with associated probabilities.

Level 3 uncertainty represents the situation in which one is able to enumerate multiple alternatives and is able to rank the alternatives in terms of perceived likelihood. That is, in light of the available knowledge and information there are several different parameterizations of the system model, alternative sets of outcomes, and/or different conceivable sets of weights. These possibilities can be ranked according to their perceived likelihood (e.g. virtually certain, very likely, likely, etc.). In the case of uncertainty about the future, Level 3 uncertainty about the future world is often captured in the form of a few trend-based scenarios based on alternative assumptions about the driving forces (e.g., three trend-based scenarios for air transport demand, based on three different assumptions about GDP growth). The scenarios are then ranked according to their perceived likelihood , but no probabilities are assigned (see, for example, Patt and Schrag (2003) and Patt and Dessai (2004)).

Level 4 uncertainty represents the situation in which one is able to enumerate multiple plausible alternatives without being able to rank the alternatives in terms of perceived likelihood. This inability can be due to a lack of knowledge or data about the mechanism or functional relationships being studied; but this inability can also arise due to the fact that the decisionmakers cannot agree on the rankings. As a result, analysts struggle to specify the appropriate models to describe interactions among the system's variables, to select the probability distributions to represent uncertainty about key parameters in the models, and/or how to value the desirability of alternative outcomes (Lempert et al. 2003).
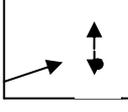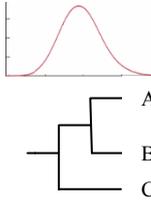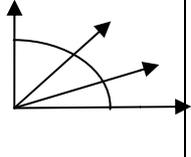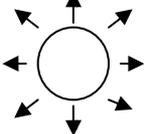
		Level 1	Level 2	Level 3	Level 4	Level 5
Context		A clear enough future (with sensitivity)	Alternate futures (with probabilities)	Alternate futures (with ranking)	A multiplicity of plausible futures (unranked)	Unknown future
Systemmodel		A single system model	A single system model with a probabilistic parameterization	Several system models, one of which is most likely	Several system models, with different structures	Unknown system model; know we don't know
Systemoutcomes		Point estimates with sensitivity	Several sets of point estimates with confidence intervals, with a probability attached to each set	Several sets of point estimates, ranked according to their perceived likelihood	A known range of outcomes	Unknown outcomes; know we don't know
Weightsonoutcomes		A single estimate of the weights	Several sets of weights, with a probability attached to each set	Several sets of weights, ranked according to their perceived likelihood	A known range of weights	Unknown weights; know we don't know

*(Left vertical label: **Complete Certainty**. Right vertical label: **Total ignorance**.)*

Figure 1-- The progressive transition of levels of uncertainty from complete certainty to total ignorance.

Level 5 uncertainty represents the deepest level of recognized uncertainty; in this case, what is knownis only that we do not know. This ignorance is recognized. Recognized ignorance is increasingly becoming a common feature of life, because catastrophic, unpredicted, surprising, but painful events seem to be occurring more often. Taleb (2007) calls these events "Black Swans". He defines a Black Swan event as one that lies outside the realm of regular expectations (i.e., "nothing in the past can convincingly point to its possibility"), carries an extreme impact, and is explainable only after the fact (i.e., through retrospective, not prospective, predictability). One of the most dramatic recent Black Swans is the concatenation of events following the 2007 subprime mortgage crisis in the United States. The mortgage crisis (which some had forecast) led to a credit crunch, which led to bank failures, which led to a deep global recession in 2009, which was outside the realm of most

expectations. Another recent Black Swan was the level 9.0 earthquake in Japan in 2011, which led to a tsunami and a nuclear catastrophe,which led to supply chain disruptions (e.g., for automobile parts) around the world.

Total ignorance is the other extreme on the scale of uncertainty. As with complete certainty, total ignorance acts as a limiting case.

Lempert et al. (2003) have defined deep uncertainty as "the condition in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes." They use the language 'do not know' and 'do not agree upon' to refer to individual and group decisionmaking, respectively. In this article we include both individual and group decisionmaking in all five of the levels, referring to Level 4 and Level 5 uncertainties as 'deep uncertainty', and assigning the 'do not know' portion of the definition to Level 5 uncertainties and the 'cannot agree upon' portion of the definition to Level 4 uncertainties.

Decisionmaking Under Deep Uncertainty

There are many quantitative analytical approaches to deal with Level 1, Level 2, and Level 3 uncertainties. In fact, most of the traditional applied scientific work in the engineering, social, and natural sciences has been built upon the supposition that the uncertainties result from either a lack of information, which "has led to an emphasis on uncertainty reduction through ever-increasing information seeking and processing"(McDaniel and Driebe, 2005), or from random variation, which has concentrated efforts on stochastic processes and statistical analysis. However, most of the important policy problems currently faced by policymakers are characterized by the higher levels of uncertainty, which cannot be dealt with through the use of probabilities and cannot be reduced by gathering more information, but are basically unknowable and unpredictable at the present time. And these high levels of uncertainty can involve uncertainties about all aspects of a policy problem — external or internal developments, the appropriate (future) system model, the parameterization of the model, the model outcomes, and the valuation of the outcomes by (future) stakeholders.

For centuries, people have used many methods to grapple withthe uncertainty shrouding the long-term future, each with its own particularstrengths. Literary narratives, generally created by one or a fewindividuals, have an unparalleled ability to capture people's imagination.More recently, group processes, such as Delphi, have helped largegroups of experts combine their expertise into narratives of the future.Statistical and computer simulation modeling helps capture quantitativeinformation about

the extrapolation of current trends and the implications of new driving forces. Formal decision analysis helps to systematically assess the consequences of such information. Scenario based planning helps individuals and groups accept the fundamental uncertainty surrounding the long-term future and consider a range of potential paths, including those that may be inconvenient or disturbing for organizational, ideological, or political reasons.

Despite this rich legacy, these traditional methods all founder on the same shoals: an inability to grapple with the long term's multiplicity of plausible futures. Any single guess about the future will likely prove wrong. Policies optimized for a "most likely" future may fail in the face of surprise. Even analyzing a well-crafted handful of scenarios will miss most of the future's richness and provides no systematic means to examine their implications. This is particularly true for methods based on detailed models. Such models that look sufficiently far into the future should raise troubling questions in the minds of both the model builders and the consumers of model output. Yet the root of the problem lies not in the models themselves but in the way in which models are used. Too often, analysts ask what will happen, thus trapping themselves in a losing game of prediction, instead of the question they really would like to have answered: Given that one cannot predict, which actions available today are likely to serve best in the future?

Broadly speaking, although there are differences in definitions, and ambiguities in meanings, the literature offers four (overlapping, not mutually exclusive) ways for dealing with deep uncertainty in making policies (see, for example, Leusink and Zanting (2009)):

- Resistance: plan for the worst conceivable case or future situation
- Resilience: whatever happens in the future, make sure that you have a policy that will result in the system recovering quickly
- Static robustness: implement a (static) policy that will perform reasonably well in practically all conceivable situations
- Adaptive robustness: prepare to change the policy, in case conditions change

The first approach is likely to be very costly and might not produce a policy that works well, because of Black Swans. The second approach accepts short-term pain (negative system performance), but focuses on recovery.

The third and fourth approaches do not use models to produce forecasts. Instead of determining the 'best' predictive model and solving for the policy that is optimal (but fragilely dependent on assumptions), in the face of deep uncertainty it may be wiser to seek among the alternatives those actions that are most robust—that achieve a given level of 'goodness' across the myriad models and assumptions consistent with known facts (Rosenhead and Mingers 2001). This is the heart of any robust decision method. A *robust policy* is defined to be one that yields outcomes that are deemed to be

satisfactory according to some selected assessment criteriaacross a wide range of future plausible states of the world. This isin contrast to an *optimalpolicy* that may achieve the bestresults among all possible plans but carries no guarantee of doingso beyond a narrowly defined set of circumstances. An analytical policy based on the concept of robustness is also closer to the actual policy reasoning process employed by senior planners andexecutive decisionmakers. As shown by Lempert and Collins (2007), analytic approaches that seek robust strategies are often appropriate both when uncertainty is deep and a rich array of options is available to decisionmakers.

Identifying static robust policies requires reversing the usual approach to uncertainty.Rather than seeking to characterize uncertainties in terms of probabilities,a task rendered impossible by definition for Level 4 and Level 5 uncertainties, onecan instead explore how differentassumptions about the future values of these uncertain variableswould affect the decisions actually being faced. Scenario planning (see, for example, van der Heijden (1996)) is one approach to identifying static robust policies. This approach assumes that, although the likelihood of the future worlds is unknown, a range of plausible futures can be specified well enough to identify a (static) policy that will produce acceptable outcomes in most of them. It works best when dealing with Level 4 uncertainties. Another approach is to ask what onewould need tobelieve was true to discard one possible policy in favor of another. This is the essence of Exploratory Modeling and Analysis (EMA) (see entry in this Encyclopedia).

Long-term robust policies for dealing with Level 5 uncertainties will generally be dynamic adaptive policies– policies that can adapt to changing conditions over time. A dynamic adaptive policy is developed with an awareness of the range of plausible futures that lie ahead, is designed to be changed over time as new information becomes available, and leverages autonomous response to surprise. Eriksson and Weber (2008) call this approach to dealing with deep uncertainty 'Adaptive Foresight'. Walker et al. (2001)have specified a generic, structured approach for developing dynamicadaptive policies for practically any policy domain. This approach allows implementation to begin prior to the resolution of all major uncertainties, with the policy being adapted over time based on new knowledge. It is a way to proceed with the implementation of long-term policies despite the presence of uncertainties. The adaptive policy approach makes dynamic adaptation explicit at the outset of policy formulation. Thus, the inevitable policy changes become part of a larger, recognized process and are not forced to be made repeatedly on an ad-hoc basis. Under this approach, significant changes in the system would be based on an analytic and deliberative effort that first clarifies system goals, and then identifies policies designed to achieve those goals and ways of modifying those policies as conditions change. Within the adaptive policy framework, individual actors would carry out their activities as they would under normal policy conditions. But policymakers and stakeholders, through monitoring and corrective actions, would try to keep the system headed toward the original goals. McCray et al. (2010) describe it succinctly as keeping policy "yoked to an evolving knowledge base."

Lempert, et al. (2003, 2006) propose an approach called 'Robust Decision Making' (RDM), which conducts a vulnerability and response option analysis using EMA to identify and compare (static or dynamic) robust policies. Walker, et al. (2001) propose a similar approach for developing adaptive policies, which they call Dynamic Adaptive Policymaking (DAP).

Some Applications of Robust Decision Making (RDM)and Dynamic Adaptive Policymaking (DAP)

RDM has been applied in a wide range of decision applications, including the development of both static and adaptive policies. One recent study (Dixon et. al. 2007) evaluated alternative (static) policies considered by the United States Congress while debating reauthorization of the Terrorism Risk Insurance Act (TRIA). TRIA provides a federal guarantee to compensate insurers for losses due to very large terrorist attacks in return for insurers providing insurance against attacks of all sizes. Congress was particularly interested in the cost to taxpayers of alternative versions of the program. The RDM analysis used a simulation model to project these costs for various TRIA options for each of several thousand cases, each representing a different combination of 17 deeply uncertain assumptions about the type of terrorist attack, the factors influencing the pre-attack distribution of insurance coverage, and any post-attack compensation decisions by the U.S. Federal government. The RDM analysis demonstrated that the expected cost to taxpayers of the existing TRIA program would prove the same or less than any of the proposed alternatives except under two conditions: the probability of a large terrorist attack (greater than $40 billion in losses) significantly exceeded current estimates *and* future Congresses did not compensate uninsured property owners in the aftermath of any such attack. This RDM analysis appeared to help resolve a divisive Congressional debate by suggesting that the existing (static) TRIA program was robust over a wide range of assumptions, except for a combination that many policymakers regarded as unlikely. The analysis demonstrates two important features of RDM: (1) its ability to systematically include imprecise probabilistic information (in this case, estimates of the likelihood of a large terrorist attack) in a formal decision analysis, and (2) its ability to incorporate very different types of uncertain information (in this case, quantitative estimates of attack likelihood and qualitative judgments about the propensity of future Congresses to compensate the uninsured).

RDM has also been used to develop adaptive policies, including policies to address climate change (Lempert et al., 1996), economic policy (Seong et al., 2005), complex systems (Lempert, 2002), and health policy (Lakdawalla et. al., 2009). A recent example illustrates RDM's ability to support practical adaptive policymaking (Groves et al., 2008; Lempert and Groves, 2010). In 2005, Southern California's Inland Empire Utilities Agency (IEUA), which supplies water to a fast growing

population in an arid region, completed a legally mandated (static) plan for ensuring reliable water supplies for the next twenty-five years. This plan did not, however, consider the potential impacts of future climate change. An RDM analysis used a simulation model to project the present value cost of implementing IEUA's current plans, including any penalties for future shortages, in several hundred cases contingent on a wide range of assumptions about six parameters representing climate impacts, IEUA's ability to implement its plan, and the availability of imported water. A scenario discovery analysis identified three key factors — an 8% or larger decrease in precipitation, any drop larger than 4% in the rain captured as groundwater, and meeting or missing the plan's specific goals for recycled waster water — that, if they occurred simultaneously, would cause IEUA's overall plan to fail (defined as producing costs exceeding by 20% or more those envisioned in the baseline plan). Having identified this vulnerability of IEUA's current plan, the RDM analysis allowed the agency managers to identify and evaluate alternative adaptive plans, each of which combined near-term actions, monitoring of key supply and demand indicators in the region, and taking specific additional actions if certain indicators were observed. The analysis suggested that IEUA could eliminate most of its vulnerabilities by committing to updating its plan over time and by making relative low-cost near-term enhancements in two current programs. Overall, the analysis allowed IEUA's managers, constituents, and elected officials, who did not all agree on the likelihood of climate impacts, to understand in detail vulnerabilities to their original plan and to identify and reach consensus on adaptive plans that could ameliorate those vulnerabilities.

An example of DAP comes from the field of airport strategic planning. Airports increasingly operate in a privatized and liberalized environment. Moreover, this change in regulations has changed the public's perception of the air transport sector. As a result of this privatization and liberalization, the air transport industry has undergone unprecedented changes, exemplified by the rise of airline alliances and low cost carriers , an increasing environmental awareness, and, since 9/11, increased safety and security concerns. These developments pose a major challenge for airports. They have to make investment decisions that will shape the future of the airport for many years to come, taking into consideration the many uncertainties that are present. DAP has been put forward as a way to plan the long-term development of an airport under these conditions (Kwakkel et al., 2010a). As an illustration, a case based on the current challenges of Amsterdam Airport Schiphol has been pursued. Using a simulation model that calculates key airport performance metrics such as capacity, noise, and external safety, the performance of an adaptive policy and a competing traditional policy across a wide range of uncertainties was explored. This comparison revealed that the traditional plan would have preferable performance only in the narrow bandwidth of future developments for which it was optimized. Outside this bandwidth, the adaptive policy had superior performance. Moreover, the analysis also revealed that the range of expected outcomes for the adaptive policy is significantly smaller than for the traditional policy. That is, an adaptive policy will reduce the uncertainty about the expected outcomes, despite various deep uncertainties about the future. This analysis strongly suggested that

airports operating in an ever increasing uncertain environment could significantly improve the adequacy of their long-term development if they planned for adaptation (Kwakkel et al., 2010b, 2010c).

Another policy area to which DAP has been applied is the expansion of the port of Rotterdam. This expansion is very costly and the additional land and facilities need to match well with market demand as it evolves over the coming 30 years or more. DAP was used to modify the existing plan so that it can cope with a wide range of uncertainties. In order to do so, adaptive policymaking was combined with Assumption-Based Planning (Dewar, 2002). This combination resulted in the identification of the most important assumptions underlying the current plan. Through the adaptive policymaking framework, these assumptions were categorized and actions for improving the likelihood that the assumptions will hold were specified (Taneja et al., 2010).

Various other areas of application of DAP have also been explored, including flood risk management in the Netherlands in light of climate change (Rahman et al., 2008) and policies with respect to the implementation of innovative urban transport infrastructures (Marchau et al. 2008), congestion road pricing (Marchau et al., 2010), intelligent speed adaptation (Agusdinata, et al., 2007), and 'magnetically levitated' (Maglev) rail transport (Marchau et al., 2010).

See **Exploratory Modeling and Analysis (EMA)**

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