15. Supporting decision making under deep uncertainty: a synthesis of approaches and techniques

Jan Kwakkel and Marjolijn Haasnoot

15.1. Introduction

Over the last decade, various researchers have put forward approaches for supporting decision making under deep uncertainty. For example, Lempert et al. (2006) put forward Robust Decision Making. This was later expanded by Kasprzyk et al. (2013) into Many-Objective Robust Decision Making. Other researchers put forward adaptive policymaking (Kwakkel et al., 2010a; Walker et al., 2001) and adaptation pathways (Haasnoot et al., 2012), which were subsequently combined into dynamic adaptive policy pathways (Haasnoot et al., 2013). At present, a variety of approaches, tools, and techniques are available, but there is little insight into how these approaches are similar or different, where they overlap, and how they might be meaningfully combined in offering decision support in a specific context. The aim of this chapter is to offer some thoughts on these questions.

Taxonomy is a study about classification of complex things

To provide a tentative, more synthetic view of the field of decision making under deep uncertainty, this chapter will first discuss the key ideas that underpin the field followed by a proposed taxonomy. These key ideas are an attempt at articulating the presuppositions that emanate from much of the literature on decision-making under deep uncertainty. They have emerged out of discussions over the last few years with various people. The taxonomy builds on an earlier taxonomy put forward by Herman et al. (2015). It tries to unravel the various approaches into the key building blocks that make up an approach. This exercise is particularly useful for it enables one to move beyond a single approach. By focusing on the building blocks that are available, analysts can start to compose context-specific approaches for supporting DMDU. Moreover, it allows academics to move away from very general statements at the level of comprehensive approaches and instead focus on specific differences and similarities at the level of building blocks.

A challenge one faces when trying to put forward a taxonomy of approaches is that they are subject to interpretation, offer quite some leeway to the user in how they are being used, and are changing over time. A taxonomy pigeonholes approaches and thus runs the risk of failing to do sufficient justice to the intrinsic flexibility that currently exists in practice with respect to DMDU-approaches. This risk is somewhat alleviated in the present case, since the focus is on the building blocks that make up the various approaches. By understanding an approach as being composed of building blocks, changes to approaches may be construed as swapping out one building block with another one.

The remainder of this chapter is organized as follows. In Section 2, a broad overview is given of the key ideas that underpin the literature on supporting DMDU. In Section 3, we present a taxonomy for the various approaches and discuss how each of the various approaches align with this taxonomy. Section 4 presents our concluding remarks.

15.2. An emerging paradigm

Decision making on complex systems requires coming to grips with irreducible uncertainty. This uncertainty arises out of intrinsic limits to predictability that occur when dealing with a complex system. Another source of uncertainty is that decision making on complex systems generally involves a variety of stakeholders with different perspectives on what the system is and what problem one is trying to solve. A third source of uncertainty is that complex systems are general subject to dynamic change and are never completely understood.

The intrinsic limits to predictability, the existence of legitimate alternative interpretations of the same data, and the limits to knowability of a system have important implications for decision making. Under the label of decision-making under deep uncertainty, these are now being explored. Deep uncertainty means that the various parties to a decision do not know or cannot agree on how the system works, how likely various possible future states of the world are, and how important the various outcomes of interest are (Lempert et al., 2003). This suggests that under deep uncertainty, it is possible to enumerate possible representations of the system, to list plausible futures, and enumerate relevant outcomes of interest without being able to rank order these representations of the system, the list of plausible futures or the enumeration of outcomes of interest in terms of likelihood or importance (Kwakkel et al., 2010b).

Is it really like that?

In the literature, there is an emerging consensus that any decision regarding a complex system should be robust with respect to the various uncertainties. Intuitively, a decision is robust if its expected performance is only weakly affected by the actual future states that emerge as a function of the values actually observed among various deeply uncertain factors. Various operationalizations of this intuition may be found in the literature (Giuliani and Castelletti, 2016; Herman et al., 2015; Kwakkel et al., 2016a; McPhail et al., 2018). On the one hand, there are robustness metrics that focus on the performance of individual policy options and assess their performance over a set of plausible futures. Well known examples include minimax and the domain criterion (Schneller and Sphicas, 1983; Starr, 1963). On the other hand, there are metrics of the performance of policy options relative to a reference point. The best known example of this type is Savage's minimax regret (Savage, 1951) which uses the best possible option for a given future as the reference point against which all other options are to be evaluated.

Over the last decade, a new decision support paradigm, known as 'decision-making under deep uncertainty', has emerged that aims to support the development of robust plans. This paradigm rests on three key ideas: (i) exploratory modeling; (ii) adaptive planning; and (iii) decision support.

15.2.1 Exploratory modeling

The first idea is exploratory modeling. In the face of deep uncertainty, one should explore the consequences of the various presently irreducible uncertainties for decision-making. Typically, in the case of complex systems this involves the use of computational scenario approaches.

The idea to systematically explore the consequences of the various uncertainties that are present is rooted in the idea of what-if scenario thinking. Scenarios are (plausible) descriptions of what the future might look like. Scenario thinking is a means for thinking about possible threats and opportunities that the future might hold and their impacts on an organization, business, or system. Scenario thinking gained prominence in part due to pioneering work by Shell in the late 1960s. One of the scenarios that emerged described a very rapid rise in oil price forcing Shell to consider futures quite different from business as usual. This was believed to give Shell a competitive advantage during the oil crisis of 1973. Thinking with scenarios when making decisions may help in choosing options that perform reasonably well under a wide range of conditions.

An example how thinking differently can help

Why is there such a strong insistence on the use of models? There is ample evidence that human reasoning with respect to complex uncertain systems is intrinsically insufficient. Often, mental models are event based, have an open-loop view of causality, ignore feedback, fail to account for time delays, and are insensitive to non-linearity (Sterman, 1994). In complex systems, the overall dynamics, however, are due to accumulations, feedbacks, and time-delays with non-linear interactions among them. Thus, mental simulations of complex systems are challenging to the point of infeasibility. This is also confirmed empirically in various studies (Atkins et al., 2002; Brehmer, 1992; Diehl and Sterman, 1995; Kleinmuntz, 1992; Sastry and Boyd, 1998; Sterman, 1989). This strongly suggests that it is worthwhile to support human reasoning on uncertain complex systems with simulation models that are much better at adequately deriving the consequences from sets of hypotheses pertaining to the functioning of these systems (Sterman, 2002).

I think that idea of using multiple models instead of one is not new. See for example Machine Learning approaches

Exploratory Modeling is a research method that uses computational experimentation for analyzing complex and uncertain systems (Bankes, 1993; Bankes et al., 2013). In the presence of deep uncertainty, the available information enables the development of a set of models, but the uncertainty precludes the possibility of narrowing down this set to a single true representation of the system of interest. A set of models that is plausible or interesting in a given context is generated by the uncertainties associated with the problem of interest and is constrained by available data and knowledge. A single model drawn from the set is not a prediction. Rather, it is a computational what-if experiment that reveals how the real-world system would behave if the specific assumptions about the various uncertainties encapsulated in this model were correct. A single what-if experiment is typically not that informative other than to suggest the plausibility of its outcomes, which in turn may contribute to the substantiation of the necessity to intervene. Instead, exploratory modeling aims to support reasoning and decision-making on the basis of a comprehensive set of such models for the system of interest. In contrast to more traditional scenario planning approaches, exploratory modeling allows reasoning over a much larger set of cases than a scenario process can generate while maintaining consistency across the set of cases. The analysis of this set of cases allows humans to infer systematic regularities among subsets of the full ensemble of cases. Thus, exploratory modeling involves searching through the set of models using (many-objective) optimization algorithms, and sampling over the set of models using computational design of experiments and global sensitivity analysis techniques.

Here models describe reality and there models use to analyze reality

Adaptive planning

The second idea underpinning many deep uncertainty approaches is the idea of adaptive planning. Adaptive planning means that plans are designed from the outset to be adapted over time in response to how the future may actually unfold. The way a plan is designed to adapt in the face of potential changes in conditions is announced simultaneously with the plan itself rather than taking place in an *ad hoc* manner *post facto*. The flexibility of adaptive plans is a key means of achieving decision robustness. While the future is unfolding, many deep uncertainties are being resolved. Having an adaptive plan allows decision makers to adapt the implementation of the plan in response to this. This means that a wide variety of futures has to be explored during plan design. Insight is needed into which actions are best suited to which futures as well as what signals from the unfolding future should be monitored to ensure the timely implementation of the appropriate actions. The timing of plan adaptation is not known a priori; it depends on how the future unfolds. In this sense, adaptive planning differs from planned adaptation, generally occurring at predetermined moments (e.g. every 5 years,) and entailing review of conditions with subsequent adaptations of the original plan. Adaptive planning involves a paradigm shift from planning in time to planning conditional on observed developments.

Decision support

The third idea is decision support. Decision making on complex and uncertain systems generally involves multiple actors coming to agreement. In such a situation planning and decision-making requires an iterative approach that facilitates learning across alternative framings of the problem, and learning about stakeholder preferences and tradeoffs, in pursuit of a collaborative process of discovering what is possible (Herman et al., 2015). In this iterative approach, the various approaches for decision-making under deep uncertainty often put candidate policy decisions into the analysis by stress testing them over a wide range of uncertainties. Next, the uncertainties are characterized by their effect on the decision. The challenges such processes pose to how decision analysis is to employed are reviewed in depth by Tsoukiàs (2008). He envisions that various decision analytic techniques are used to enable a constructive learning process amongst the stakeholders and analysts. Decision analysis in this conceptualization should shift from the *a priori* agreement on (or imposition of) assumptions about the probability of alternative states of the world and the way in which competing objectives are to be aggregated with the aim of producing a preference ranking of decision alternative, to an *a posteriori* exploration of trade-offs amongst objectives and the robustness of this performance across possible futures. Decision support should move away from trying to define what is the right choice and instead aim at enabling deliberation and joint sense making amongst the various parties to decision.

15.3 A taxonomy of approaches for supporting decision making under deep uncertainty

The availability of a variety of approaches for supporting the making of decisions under deep uncertainty raises a new set of questions. How are the various approaches different? Where do they overlap? Where are they complementary? Answering these questions may help pave the way for the future harmonization and potential integration of these various approaches. It might also help in assessing if certain approaches are more applicable in certain decision-making contexts than others. Both Hall et al. (2012) and Matrosov et al. (2013b) compare Info-Gap Decision Theory and Robust Decision-Making. They conclude that along quite different analytical paths, both approaches arrive at fairly similar but not identical results. Matrosov et al. (2013a) compare Robust Decision-Making with an economic optimization approach. In this case, the results from applying both techniques yield different analytical results, suggesting value to efforts seeking to combine both approaches. Roach et al. (2015) and Roach et al. (2016) compare Info-Gap Decision Theory and robust optimization. They conclude that there are substantial differences between the plans resulting from these two approaches and argue in favor of mixed methodologies. Gersonius et al. (2015) compare a real options analysis (in detail reported in Gersonius et al., 2013) with an adaptation tipping point analysis (Kwadijk et al., 2010). They highlight the substantial differences in starting points and suggest that both approaches could be applied simultaneously. Essentially the same is argued by Buurman and Babovic (2016), who compared DAPP and real options analysis. Kwakkel et al. (2016b) compared DAPP and RDM. They argue in favor of combining both approaches. DAPP primarily provides a systematic structure for adaptive plans, while RDM provides a clear iterative model-based process for designing adaptive plans.

To move beyond a discussion of the exact communalities and differences amongst the various DMDU-approaches, a taxonomy of the components that make up the approaches is useful. A first such taxonomy was put forward by (Herman et al., 2015). This taxonomy focused on model-based robustness frameworks for supporting decision making under deep uncertainty. In light of the foundational ideas introduced in the previous section, one could say that the Herman taxonomy focused exclusively on exploratory modeling. The purpose of this chapter, however is to cover the broader field and not restrict ourselves to exploratory modeling approaches exclusively. Practically, this means that there is a need to supplement the Herman taxonomy with an additional category related to adaptive planning (the second foundational idea).

Figure 15.1 shows the proposed taxonomy of approaches for supporting the making of decisions under deep uncertainty. It covers five broad categories:

1. **Policy architecture;** which covers the various ways in which adaptive policies may be structured.
2. **Generation of policy alternatives;** which covers how policy alternatives, or components thereof are being identified, given a specification of the available policy levers.
3. **Generation of scenarios**; which covers how context scenarios are being identified given a variety of uncertainties.
4. **Robustness metrics**; which covers the various ways in which policy robustness is being operationalized.
5. **Vulnerability analysis**; which covers the various analysis techniques that are being used to understand how policy robustness is influenced by both uncertainties and policy levers.

In the following subsections we discuss each of these categories in more detail.

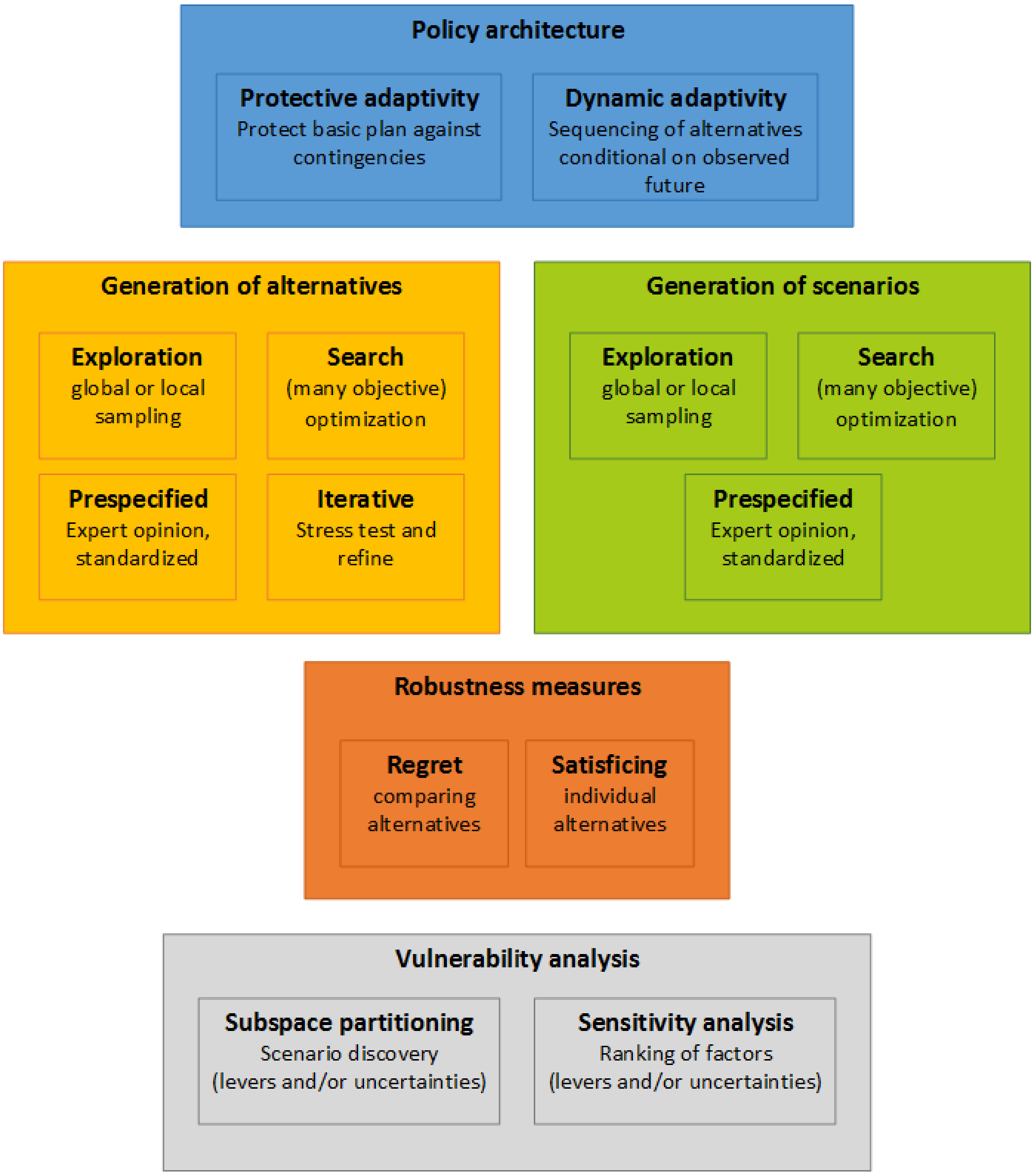

Figure 15.1 A taxonomy of approaches for supporting the making of decisions under deep uncertainty

15.3.1 Policy architecture

In the deep uncertainty literature and before, various ideas on adaptive plans or policies and the importance of flexibility in planning and decision-making can be found. Under deep uncertainty, static plans are likely to fail, become overly costly to protect against failure, or incapable of seizing opportunities. An alternative is to design flexible plans that can be adapted over time. In this way, a policy may be yoked to an evolving knowledge base (McCray et al., 2010). Adaptive actions are implemented only if in monitoring how the various uncertainties are resolving there is a clear signal that these actions are needed.

Signals can come both from monitoring data as well as from computer simulations of future developments. Many examples of authors arguing in favor of this paradigm may be found. (Albrechts, 2004; Eriksson and Weber, 2008; Kwakkel et al., 2010a; Lempert et al., 2003; Neufville and Odoni, 2003; Schwartz and Trigeorgis, 2004; Swanson et al., 2010; Walker et al., 2001).

The initial seeds for the adaptive planning paradigm were sown almost a century ago. Dewey (1927) put forth an argument proposing that policies be treated as experiments with the aim of promoting continual learning and adaptation in response to experience over time (Busenberg, 2001). Early applications of this idea can be found in the field of environmental management (Holling, 1978; McLain and Lee, 1996) where because of the uncertainty about system functioning policies are designed from the outset to test clearly formulated hypotheses about the behavior of an ecosystem being changed by human use (Lee, 1993). A similar attitude is also advocated by Collingridge (1980) with respect to the development of new technologies. Given ignorance about the possible side effects of technologies under development, he argues that one should strive for correctability of decisions, extensive monitoring of effects, and flexibility. Policy learning is also major issue in evolutionary economics of innovation (De La Mothe, 2006; Faber and Frenken, 2009; Mytelka and Smith, 2002).

An example

How about the example from ethics class on the absence of post monitoring of the projects even here, in the Netherlands!

More recently, Walker et al. (2001) developed a structured, stepwise approach for dynamic adaptation. Walker et al. (2001) advocate that policies should be adaptive: one should take only those actions that are non-regret and time-urgent, and postpone other actions to a later stage. They suggest that a monitoring system and a pre-specification of responses when specific trigger values are reached should complement a basic policy. The resulting policy is flexible and adaptive to the future as it unfolds. The idea of adaptive policies was extended further by Haasnoot et al. (2012), who conceptualized a plan as a sequence of actions to be realized over time. In later work, they called this adaptive policy pathways (Haasnoot et al., 2013).

Seems to be super reactive planning?

A policy architecture is the overarching structure that is used to design a plan. A range of adaptive policy architectures is possible. At one extreme, we have a basic plan to be implemented immediately, complemented by a set of contingency actions that are to be implemented if and when necessary. This is the style of policy architecture implicitly advocated in Assumption-Based Planning (Dewar, 2002; Dewar et al., 1993). Adaptive policymaking (Kwakkel et al., 2010a; Walker et al., 2001) also sits in this corner (Figure). The other extreme no longer mandates a single overarching set of actions to be implemented immediately. Instead, policies are seen as series of actions the implementation of which co-evolve with how the future unfolds. Dynamic adaptive policy pathways (Haasnoot et al., 2013) exemplify this type of policy architecture (Figure).

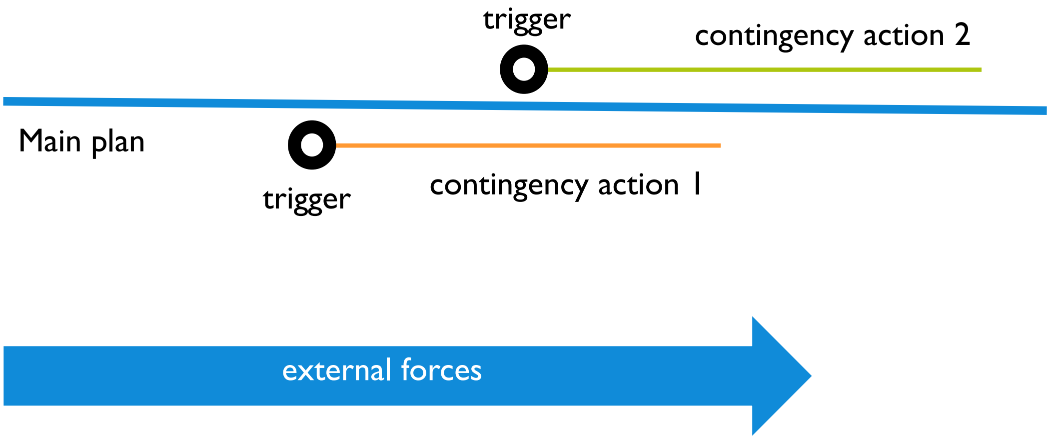

Figure 15.2 Adaptive policy

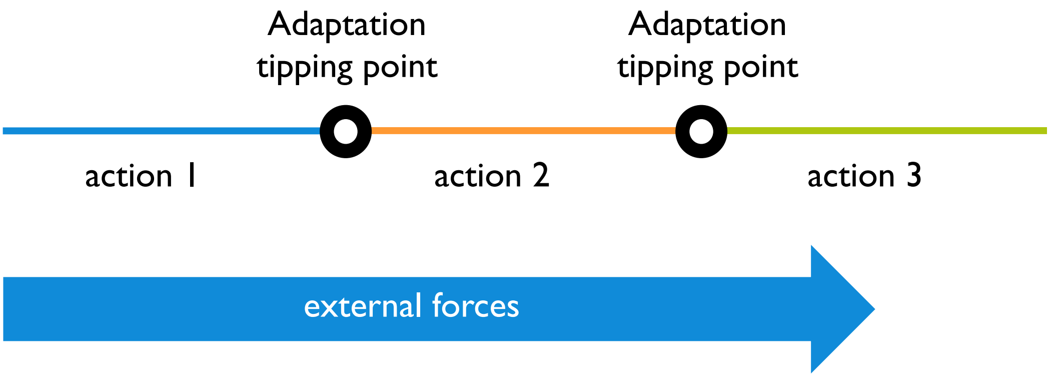

Figure 15.3 Adaptation pathway

15.3.2 Generation of scenarios and candidate strategies

Given a wide variety of deeply uncertain factors, and a set of policy levers that may be used to steer the system towards more desirable functioning, the analyst has to choose how to investigate the influence of both uncertainties and levers on outcomes. Broadly speaking a distinction can be drawn between two different strategies: exploration and search. Exploration strategies investigate the properties of the uncertainty space and the policy levers space by systematically sampling points in this space and evaluating their consequences. Exploration relies on the careful design of experiments and can use techniques such as

Monte Carlo sampling, Latin Hypercube sampling, or factorial methods. Exploration may be used to answer questions such as "under what circumstances would this policy do well?", "under what circumstances would it likely fail?", and "what dynamics could this system exhibit?". Exploration provides insight into the global properties of the uncertainty space and the policy levers space.

In contrast, optimization-based approaches hunt through the space in a more directed manner in search of points with particular properties. Search may be used to answer questions such as "What is the worst that could happen?", "What is the best that could happen?", "How big is the difference in performance between rival policies?", "What would a good strategy be given one or more scenarios?" Search provides detailed insights into particular points in the uncertainty space or policy levers space. Search relies on the use of (many objective) optimization techniques.

A third possibility is to have predefined scenarios or policies, instead of requiring systematic investigation of the whole uncertainty space and policy lever space. For example, in its original inception, Robust Decision Making assumes that a set of candidate policies is pre-specified. The performance of these policies is then investigated over a wide range of scenarios. Here, the focus of the exploration is on the impact of the uncertainties on the performance of the pre-specified policies.

In practice, the different strategies for investigating the impacts of uncertainties and policy levers can be combined as well as executed in an iterative manner. For example, if exploration reveals that there are distinct regions in which a policy fails, search may be employed to identify more precisely where the boundary is located between these distinct regions. Another example is to use exploration to identify the conditions under which a policy fails and use this insight to modify the policy. By iterating, a policy can be designed that performs acceptably under a wide range of possible future conditions. Robust Decision Making, for example, strongly emphasises the iterative refinement of candidate policies.

Robustness

A well-established distinction regarding robustness metrics is the distinction between regret metrics and satisficing metrics (Lempert and Collins, 2007). Regret metrics are comparative and originate from Savage (1954) who defines the regret of a policy option as the difference between the performance of the option in a specific state of the world and the performance of the best possible option in that state of the world. A robust policy option is one that minimizes the maximum regret across the states of the world (SOWs). Alternative regret metrics use some type of baseline performance for a given state of the world instead of the performance of the best option (Kasprzyk et al., 2013; Lempert and Collins, 2007; Popper et al., 2009).

Satisficing metrics build on the work of Simon (1996), who pointed out that decision makers often look for a decision that meets one or more requirements, but may not achieve the optimal possible outcomes. Satisficing metrics aim at maximizing the number of states of the world in which the policy option under consideration meets a minimum performance threshold. A well-known example of this is the domain criterion (Schneller and Sphicas, 1983; Starr, 1963), which focuses on the fraction of the space in which a given performance threshold is met; the larger this space, the more robust the policy option. Often, this is simplified to looking at the fraction of states of the world, rather than the volume of the space.

Synthesizing the foregoing, in defining robustness an analyst must make two choices. The first choice is about the policy options. Is the analyst interested in the performance of individual policy options or is she interested in comparing the performance of options? Out of this choice comes a distribution of performance of each policy option over the set of states of the world. The second choice is how to succinctly describe this distribution. Here the analyst also has two options: she may impose some user-specified performance threshold or characterize the distribution using descriptive statistics.

Table 15.2. Conceptual representation of various robustness metrics

		Characterizing performance of policy options	
		Comparing options	**Performance of individual options**
Characterizing performance over SOW	**Threshold**	Satisficing regret	Domain criterion (Starr, 1963), radius of stability, info-gap (Ben Haim, 2001)

Descriptive statistics	Minimax regret (Savage, 1954), 90th percentile baseline regret (Kasprzyk et al., 2013), 90th percentile best option regret (Herman et al., 2015)	Moments of the distribution (e.g. mean, variance) minimum, maximum, and functions thereof (Hurwicz, signal-to-noise, coefficient of variation)

Many of the classic decision analytic robustness metrics belong to the lower right hand corner: they focus on the performance of individual policy options and try to describe the performance of a policy option over the set of states of the world using descriptive statistics. Maximin and minimax focus on the best and worst performance over the set of scenarios, while Hurwicz is a function of both. Similarly, Laplace's principle of insufficient reason assigns an equal weight to each of the states of the world and then suggests that the best decision is the one with the best mean performance. More recently, there has been interest in using higher order moments as well. Hamarat et al. (2014) use a signal-to-noise ratio that considers both the average and the variance. A problem here is that combinations of the mean and variance are not always monotonically increasing (Ray et al., 2013). Moreover, focusing on variance or the standard deviation means that good and bad deviations from the mean are treated equally (Takriti and Ahmed, 2004). This explains why higher order moments, skewness and kurtosis, have attracted attention (Kwakkel et al., 2016a).

Vulnerability analysis

Vulnerability analysis is often used in combination with an exploration strategy for the generation of scenarios. That is, exploration is used to generate an ensemble of scenarios. Then one or more alternative policies are evaluated over those scenarios with vulnerability analysis being used to discover the influence the various uncertainties have on the success or failure of these strategies. However, the vulnerability analysis techniques need not be restricted to understanding the role of the uncertainties. They can equally well be used to investigate the role of the policy levers.

Broadly speaking, two distinct styles of vulnerability analysis are being used. On the one hand, we can use global sensitivity analysis to identify the relative importance of the various uncertainties or policy levers on the outcomes of interest. As Herman et al. (2015) point out, this is an underutilized technique in the deep uncertainty literature. Global sensitivity analyses techniques can serve various functions in the context of a deep uncertainty study. They may be used for factor prioritization—that is, to identify the relative influence of the various uncertainties or policy levers on the outcomes of interest. This helps reduce the dimensionality of the problem by focusing subsequent analyses on the key sources of uncertainties or to search over the most influential policy levers. The results of a sensitivity analysis may also enhance understanding of which uncertainties really matter. This is valuable information for designing policies–for example, by designing strategies that capable of adaptation conditional on how these uncertainties resolve over time, or by designing strategies that have a reduced sensitivity to these factors. See Herman et al. (2014) for some examples of the usefulness of global sensitivity analyses for supporting the making of decisions under deep uncertainty.

On the other hand, we can try to find particular subspaces in either the uncertainty space or the policy-lever space that result in a particular class of model outcomes. A well-established approach for this is scenario discovery in which one tries to find subspaces of the uncertainty space for which a candidate policy fails. Adaptation tipping points, a concept central to adaptive policy pathways, are essentially the same: an adaptation tipping point specifies the uncertain conditions under which the existing actions on the pathway fail to achieve the stated objectives. Decision Scaling also employs a similar idea. In all three cases, the analyst tries to partition the uncertainty space into distinct regions based on the success or failure of a candidate strategy.

Application of the taxonomy

Table 15.3 contains a summary overview of the various approaches and techniques for DMDU using the typology presented in Figure 15.1. Robust Decision Making does not explicitly put forward a policy architecture. In most of its applications, however, it uses a form of protective adaptivity, drawing on ideas from Assumption-Based Planning (ABP) and adaptive policymaking. For the generation of scenarios, it uses sampling. Strategies typically are pre-specified and iteratively refined. RDM uses a domain criterion in the vulnerability phase, while it closes with a regret-based analysis of the leading decision alternatives. For the vulnerability analysis, RDM uses scenario discovery. MORDM uses the RDM structure, but replaces pre-specified alternatives with a many-objective search for a reference scenario. The advantage of this is that the set of initial decision alternatives resulting from this process have good performance and represent a careful exploration of the design space.

Three approaches that primarily emphasize the policy architecture are Assumption-Based Planning, adaptive policymaking, and adaptation pathways.

They represent opposing ends of the spectrum of adaptive policy architectures. ABP and adaptive policymaking focus on the use of adaptivity to protect a basic plan from failing. ABP relies primarily on qualitative judgments. Adaptive policymaking says little with respect to how to use models for designing adaptive polices. Hamarat et al. (2013) use RDM for this. In contrast, dynamic adaptive policy pathways can only be assembled from a given set of actions. These thus need to be found first. In most applications of DAPP, the actions are assumed to be given. For vulnerability analysis, DAPP uses adaptation tipping points, which can be seen as a one-dimensional version of scenario discovery.

Scenario discovery, adaptation tipping points, Decision Scaling, and Info-gap Decision Theory are essentially vulnerability analysis techniques that may be used to design adaptive plans. Of these, scenario discovery is the most general form. Adaptation tipping point analysis is, in essence, a one-dimensional scenario discovery. Similarly, Decision Scaling is a one- or at most two-dimensional form of scenario discovery exclusively focused on climate information. All three focus on finding subspace(s) of the uncertainty space for which a policy fails. For adaptation tipping points and Decision Scaling, this subspace is characterized by climate change information. Scenario discovery is agnostic with respect to the uncertainties to be considered. Info-gap is a bit different in this respect, since it requires a reference scenario from which the radius of stability is calculated. As such, it does not produce insight into the subspace in which a policy fails but instead into how far the future is allowed to deviate from the reference scenario before a policy starts to fail. This means that the choice of the reference scenario and the distance metric used become analytical issues.

Many-objective robust optimization is a generic approach for designing adaptive plans. It has been used in combination with both adaptive policymaking (Hamarat et al., 2014) and adaptive policy pathways (Kwakkel et al., 2015). It extends the argument found in the MORDM literature on the relevance of finding promising designs prior to performing in depth analyses by bringing robustness considerations into the search itself. Because of this, it does not include a vulnerability analysis.

Table 15.3 Application of the typology to various approaches and techniques for supporting the making of decisions under deep uncertainty

	Key references	Policy architecture	Generation of scenarios	Generation of candidate strategies	Robustness	Vulnerability analysis
Robust Decision Making	(Hamarat et al., 2013; Lempert et al., 2006)	Not explicitly considered, but often combined with protective adaptivity	Sampling	Generally pre-specified, and iteratively refined	The scenario discovery phase uses a satisficing metric (domain criterion), while the trade-off analysis phase relies on regret	Scenario discovery (Bryant and Lempert, 2010; Kwakkel and Jaxa-Rozen, 2016)
Many Objective Robust Decision Making	(Kasprzyk et al., 2013; Watson and Kasprzyk, 2017)	Not explicitly considered	Sampling	Many-objective search for one or a few scenarios separately	The scenario discovery phase uses a satisficing metric (domain criterion), while the trade-off analysis phase relies on regret	Scenario discovery
Adaptive Policy-Making	(Kwakkel et al., 2010a; Walker et al., 2001)	Protective adaptivity	Not explicitly considered	Not explicitly considered	Typically focused on satisficing measures	Not explicitly considered
Dynamic Adaptive Policy Pathways	(Haasnoot et al., 2013; Haasnoot et al., 2012)	Transformative adaptivity	Not explicitly considered, but strong emphasis on the need for transient scenarios	Typically pre-specified	Typically focused on satisficing measures	Adaptation tipping points (Kwadijk et al., 2010)

Assumption-Based Planning	(Dewar, 2002; Dewar et al., 1993)	Protective adaptivity	Not considered; focus is on assumptions that might fail, not on scenarios where they might fail	Pre-specified	Typically focused on satisficing measures	Qualitative judgment
Scenario Discovery	(Bryant and Lempert, 2010; Groves and Lempert, 2007; Kwakkel and Jaxa-Rozen, 2016)	Not considered	Sampling	Typically pre-specified	Domain criterion (implicit)	Dedicated vulnerability technique in itself
Adaptation Tipping Points	(Kwadijk et al., 2010)	Not considered	Pre-specified, or sampling	Typically pre-specified	Satisficing (domain criterion)	Dedicated vulnerability technique in itself
Info-gap Decision Theory	(Ben Haim, 2001, 2004)	Not considered	Sampling outward from a reference scenario	Pre-specified	Satisficing (Radius of stability)	Not considered
Decision Scaling	(Brown et al., 2012; LeRoy Poff et al., 2015)	Not considered	Pre-specified, or sampling constrained by climate information	Pre-specified	Satisficing (domain criterion)	Climate Response Function (visual), ANOVA ranking
Engineering Options Analysis	(de Neufville and Scholtes, 2011)			Pre-specified		
Many Objective Robust Optimization	(Hamarat et al., 2014; Kwakkel et al., 2015)	Not considered, can be used for both	Pre-specified, or sampling	Many-objective search	Compatible with all satisficing metrics,	Not considered

	protective and transformative adaptivity		and reference scenario regret

Concluding remarks

This chapter has presented a taxonomy of the various approaches and techniques for supporting the making of decisions under deep uncertainty. In short, there are 5 categories: policy architecture, generation of scenarios, generation of alternatives, the definition of robustness, and vulnerability analysis. Any given approach for decision-making under deep uncertainty makes choices with respect to these five categories. For some, these choices are primarily or almost exclusively in one category while remaining silent on the others. For other approaches, implicit or explicit choices are made with respect to each category. Table 15.3 in the previous section summarizes this.

Going forward, it might be useful to use the typology to articulate which choices are made in a given case rather than having to argue over the exact differences between approaches and the merits of these differences. That is, rather than arguing over whether to apply RDM or DAPP, the discussion should be which combination of deep uncertainty techniques are appropriate to use given the nature of the problem situation. Different situations warrant different combinations. For example, when designing a new piece of infrastructure, say a large reservoir, it makes sense to use many-objective search for finding promising design alternatives prior to performing a vulnerability analysis. In other cases, a set of decision options or combinations thereof might already be available. In such a case, doing additional search might be less relevant.

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