# Adapt or Perish: An Approach to Planning Under Deep Uncertainty

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# Adapt or Perish: An Approach to Planning Under Deep Uncertainty

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**ABSTRACT**

Much policy advice is formulated implicitly assuming that the future can be predicted. A static policy is developed using a single 'most likely' future, often based on the extrapolation of trends; or a static 'robust' policy is developed that will produce acceptable outcomes in a range of plausible future worlds. However, if the future turns out to be different from the hypothesized future(s), the policy might fail. Furthermore, not only is the future highly uncertain, the conditions policymakers need to deal with are changing over time. This paper begins by defining what is meant by 'deep uncertainty'. It then describes a new approach for planning under conditions of deep uncertainty that is based on creating a strategic vision of the future, committing to short-term actions, and establishing a framework to guide future actions. A policy that embodies these ideas allows for its dynamic adaptation over time to meet the changing circumstances.

**KEYWORDS:** deep uncertainty; robust decision making; adaptive policies; adaptation pathways; exploratory modeling and analysis

## 1. THE POLICYMAKING PROBLEM

The world is undergoing rapid changes. The future is uncertain. Policymakers are faced with policy alternatives that are often numerous, diverse, and produce multiple consequences that

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[1] Sont également issues de cette table ronde les contributions suivantes :

- Fusco, Bertoncello et al. : ***Faire science avec l'incertitude : réflexions sur la production des connaissances en SHS.*** [https://halshs.archives-ouvertes.fr/halshs-01166287]
- Tuffery, Fernandes et al. : ***Evaluation des domaines d'incertitude et de leur éventuelle diminution dans un projet collectif de recherche interdisciplinaire : le cas du PCR « Réseau de lithothèques en Rhône-Alpes ».*** [https://halshs.archives-ouvertes.fr/halshs-01166167]
- Bianchi et Labory : ***The role of governance and government in the resilience of regions: the case of the 2012 earthquake in the Emilia-Romagna region in Italy.*** [https://halshs.archives-ouvertes.fr/halshs-01166138]
- Rinaudo : ***Le traitement de l'incertitude dans la relation d'enquête ethnographique en Sciences sociales.*** [https://halshs.archives-ouvertes.fr/halshs-01166138]
- Boissinot : ***Archéologie et incertitude.*** [https://halshs.archives-ouvertes.fr/halshs-01166149]

are far-reaching yet difficult to anticipate (let alone predict). Different groups perceive and value different consequences differently. Nevertheless, public policymakers have a responsibility to develop and implement policies that have the best chance of contributing to the health, safety, and well being of their constituencies.

Given this context, policymaking is not easy. Uncertainties abound. Data are limited. Simply identifying the key policy issues is a difficult task; and one does not have the luxury of ignoring certain topics because they are too messy or intractable. However, without analysis, important policy choices are based on hunches and guesses -- sometimes with regrettable results.

A major challenge in designing successful plans is the requirement to accept, understand, and manage uncertainty, since:

- not all uncertainties about the future can be eliminated;
- ignoring uncertainty could mean that we limit our ability to take corrective action in the future and end up in situations that could have been avoided; and
- ignoring uncertainty can result in missed chances and opportunities, and lead to the failure of the plan.

Most of the traditional applied scientific work in the engineering, social, and natural sciences has been built on the supposition that the uncertainties result from 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 strategic planning problems currently faced by decisionmakers are characterized by uncertainties about the future that cannot be reduced by gathering more information and are not statistical in nature (Walker et al., 2013a). The uncertainties are unknowable at the present time, but will be reduced over time. They can involve uncertainties about all aspects of a long-term strategic planning problem—external developments, the appropriate (future) system model, and the valuation of the model outcomes by (future) stakeholders. Such situations have been characterized as having "deep uncertainty"—defined as a situation 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" (Walker et al., 2013a; Lempert et al., 2003).

Although policy analysts and strategic planners are aware that they are facing deep uncertainty, most of them still develop plans based on the assumption that the future can be predicted. They develop a static "optimal" plan using a single "most likely" future, often based on the extrapolation of trends, or a static "robust" plan that will produce acceptable outcomes in a small number of hypothesized future worlds. (Some call this the 'predict-and-act approach (Walker et al., 2013b, p. 232)). However, if the future turns out to be different from the hypothesized future(s), the plan is likely to fail. Furthermore, the world is continuously changing, so the conditions planners need to deal with are continuously changing. Therefore, plans need to be adapted to meet these changing conditions. But, it is rare that such adaptation has been planned for in advance.

Any single guess about the future is likely to prove wrong. The performance of plans optimized for a most likely future can deteriorate very quickly due to small deviations from the most likely future, let alone 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 (Annema and de Jong, 2011; Dessai and Hulme, 2008; Goodwin and Wright, 2010). This is particularly true for methods based on detailed models. Models that look far into the future should raise troubling questions about their assumptions and their validity in the minds of both the model builders and the consumers of their output. Yet the root of the problem lies not in the models themselves, but in the way in which they 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?"

## 2. THE FOUR LEVELS OF UNCERTAINTY

Generally speaking, uncertainty is defined as limited or inadequate information (Walker et al. 2013b). Uncertainty can derive from natural variability within a system (aleatory uncertainty) or from lack of knowledge (epistemic uncertainty). The definition of uncertainty may then be broadened to "any departure from the unachievable ideal of complete determinism" (Walker et al., 2003).

In order to manage uncertainty, one must be aware that an entire spectrum of different levels of knowledge exists, ranging from the unachievable ideal of complete understanding at one end of the scale to total ignorance at the other. Policy analysts have different methods and tools to treat the various levels. For purposes of determining ways of dealing with uncertainty in developing plans, one can distinguish two extreme levels of uncertainty (complete certainty and total ignorance) and several intermediate levels. Walker et al. (2003) have defined four intermediate levels:

- Complete certainty is the situation in which we know everything 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. 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 plausible futures without being able to assign probabilities to them.
- Level 4 uncertainty represents the deepest level of recognized uncertainty; in this case, we know only that we do not know. We recognize our ignorance. Recognized ignorance is increasingly becoming a common feature of our existence, 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).
- Total ignorance is the other extreme on the scale of uncertainty. As with complete certainty, total ignorance acts as a limiting case.

Level 4 uncertainty is what we have called 'deep uncertainty' (Walker et al., 2013a). To repeat the definition in Sec.1 above, deep uncertainty is a situation in which "analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe the interactions among a system's variables, (2) the probability distributions to represent uncertainty about key variables and parameters in the models, and/or (3) how to value the desirability of alternative outcomes".

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 sustainable plans (Walker et al., 2013a):

- resistance: plan for the worst possible case or future situation

- resilience: whatever happens in the future, make sure that the system can recover quickly
- static robustness: aim at reducing vulnerability in the largest possible range of conditions
- dynamic robustness (or adaptivity): plan to change over time, in case conditions change

The first approach is likely to be very costly and might not produce a plan that works well, because of unanticipated surprises ('Black Swans'). The second approach accepts short-term pain (negative system performance), but focuses on recovery. Unlike most approaches for dealing with Level 1 and Level 2 uncertainties, the third and fourth approaches do not use models to produce forecasts. Instead of determining the best predictive model and solving for the plan that is optimal, but fragilely dependent on assumptions (as is done by approaches for dealing with Level 1 and Level 2 uncertainties), in the face of deep uncertainty it may be wiser to seek among the alternatives those actions that are most robust—that achieve a reasonable level of goodness across the myriad models and assumptions consistent with the known facts. As shown by Lempert and Collins (2007), analytic approaches that seek robust plans are often appropriate when uncertainty is deep and a rich array of options is available to decisionmakers.

Identifying robust plans 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 3 and Level 4 uncertainties, one can instead explore how different assumptions about the future values of these uncertain variables would affect the decisions actually being faced. Scenario planning (van der Heijden 1996) is one approach to identifying static robust plans. This approach assumes that, although the likelihood of various future worlds is unknown, a range of plausible futures can be specified well enough to identify a (static) plan that will produce acceptable outcomes in most of them. It works best when dealing with Level 3 uncertainties.

Long-term robust plans for dealing with Level 4 uncertainties will generally need to be truly adaptive – i.e., plans that can be easily changed in response to changing conditions. An adaptive plan 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.

This paper deals with dynamic robustness to reach a plan that can adapt to changing conditions and, therefore, is well suited to situations involving deep uncertainty. Changes in the plan become part of a larger, recognized process, and are not forced to be made repeatedly on an *ad-hoc* basis. Planners, through monitoring and corrective actions, keep the system headed toward the original goals. The approach is called Dynamic Adaptive Planning (DAP). Central to DAP is the acknowledgement of uncertainty: that in a rapidly changing world, fixed static policies are likely to fail. As new information becomes known over the life of a policy or plan, it should incorporate the ability to adapt dynamically through learning mechanisms.

## 3. DYNAMIC ADAPTIVE PLANNING

DAP was first outlined by Walker, et al. (2001), and made more concrete by Kwakkel et al. (2010). This planning paradigm, in one form or another, has been receiving increasing attention in various policy domains. Dynamic flexible plans are being developed for water management of New York (Rosenzweig et al., 2010), New Zealand (Lawrence and Manning 2012), and the Rhine Delta (Jeuken and Reeder, 2011), and have been developed for the Thames Estuary (Reeder and Ranger, 2011; Ranger et al. 2013). DAP has also been explored in various applications, 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), airport strategic planning (Kwakkel et al., 2010), and ‘magnetically levitated’ (Maglev) rail transport (Marchau et al., 2010).

In brief, DAP involves developing a basic plan, identifying the vulnerabilities of the plan (i.e., how it might fail), developing a series of actions to guard against these vulnerabilities, and establishing a series of signposts to monitor the uncertain vulnerabilities. During implementation, if the monitoring program indicates that one or more of the signposts reaches predetermined critical levels, predetermined adaptive actions are taken to ensure that the basic plan stays on track to meet its goals and objectives. The basic plan, monitoring program, and planned adaptations remain in place unless monitoring indicates that the intended outcomes can no longer be achieved, or if the goals and objectives of the basic plan change. In these instances, the adaptive plan is then reassessed. The elements of flexibility, adaptability, and learning enable DAP to adjust to new information as it becomes available, and therefore to deal with deep uncertainty.

DAP occurs in two phases: (1) a design phase, in which the dynamic adaptive plan, monitoring program, and various pre- and post-implementation actions are designed, and (2) an implementation phase, in which the plan and the monitoring program are implemented and adaptive actions are taken, if necessary. The five steps of the design phase are shown in

Figure 1. Once the basic dynamic adaptive plan is established through the five design steps shown, the plan is implemented, and monitoring commences.

**Step I (Stage Setting) & Step II (Assembling a Basic Plan)**

As a foundation for the plan, the goals and objectives that are important to the planners and stakeholders are defined, as is what constitutes a successful outcome. Planning constraints are identified and a series of basic options are analyzed. In Step II, the basic plan that meets the goals and objectives is assembled from the options that have been identified. The necessary conditions for success are outlined (e.g., physical, political, economic, or other conditions necessary for the plan to succeed). It is important in this step to identify a full range of necessary conditions for success, as these are used in later steps to identify vulnerabilities, signposts, and triggers. For this reason, it is important to involve managing agencies, as well as other stakeholders.

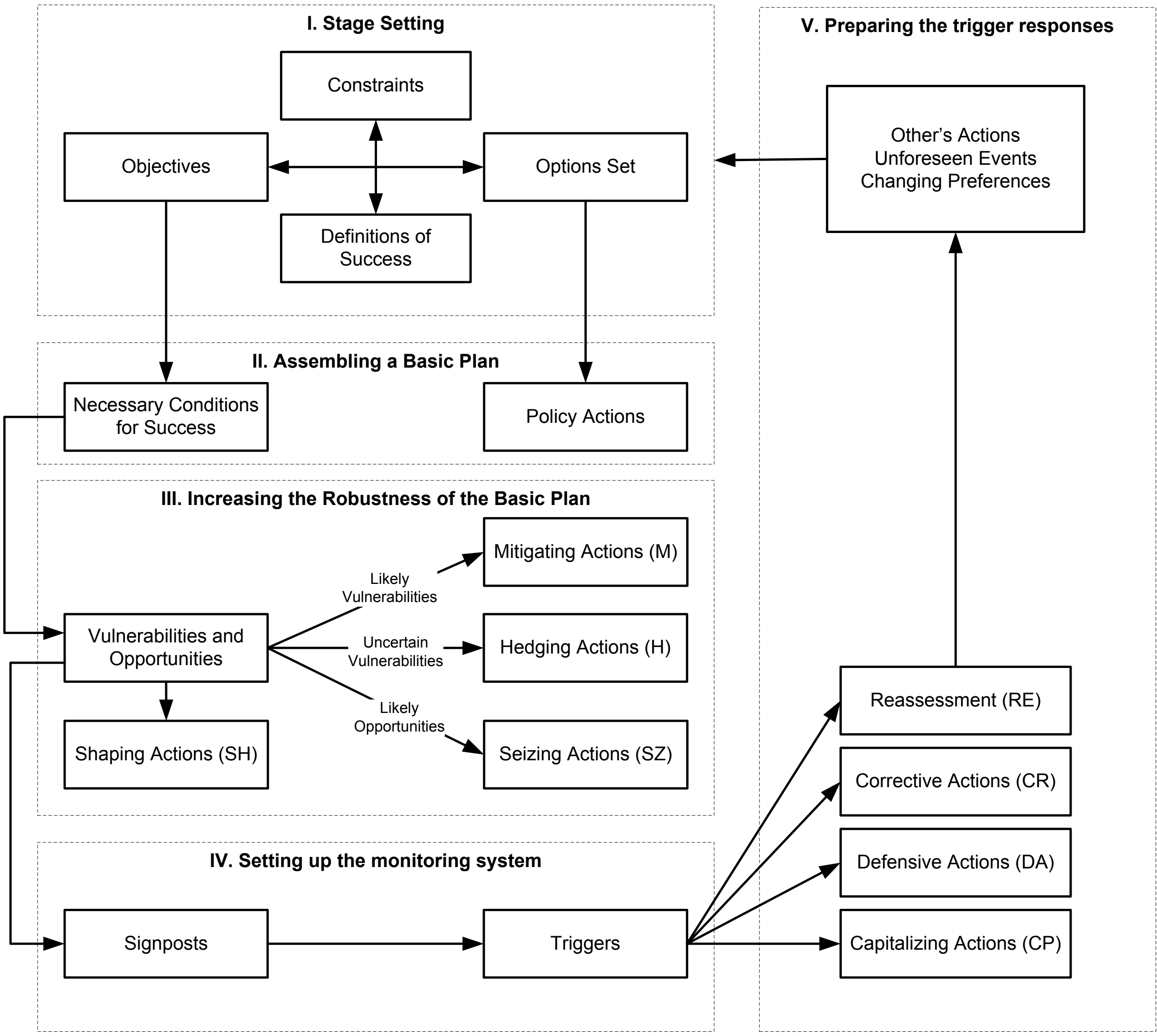


**Figure 1. Five-step process of Dynamic Adaptive Planning (Walker et al., 2013b, p. 244)**

**Step III (Increasing the Robustness of the Basic Plan)**

The static robustness of the basic plan is increased through a series of actions taken in direct response to vulnerabilities and opportunities. Vulnerabilities that can diminish the success of the basic plan, and opportunities that can increase the success of the basic plan, are first identified. Analytical tools, such as Exploratory Modeling and Analysis (EMA) (Bankes et al. 2013) or scenario analysis (van der Heijden, 1996) may be used to investigate plausible future conditions to ensure that relevant vulnerabilities, particularly uncertain vulnerabilities, are identified. An approach based on EMA, called Scenario Discovery (Bryant and Lempert, 2010; Kwakkel et al., 2012), can be used to identify the scenarios in which a plan would perform poorly. These scenarios highlight the vulnerabilities of the plan. Then, actions can be specified to protect the plan from failing if these scenarios occur.

Four types of actions can be taken immediately upon implementation of the plan to address these vulnerabilities (and opportunities). These four types of actions are (Walker et al., 2013b):

- **Mitigating actions (M)** – Actions that reduce adverse impacts on a plan stemming from *likely* vulnerabilities.
- **Hedging actions (H)** – Actions that reduce adverse impacts on a plan, or spread or reduce risks that stem from *uncertain* vulnerabilities.
- **Seizing actions (SZ)** – Actions that take advantage of opportunities that may prove beneficial to the plan.
- **Shaping actions (SH)** – Actions taken proactively to affect external events or conditions that could either reduce the plan's chance of failure or increase its chance of success.

**Step IV (Setting up the Monitoring System)**

A monitoring program is developed that will identify and initiate responses to new conditions over the course of the plan. This constitutes the learning component that gives DAP the flexibility to adapt to new conditions over time. This introduces the element of adaptive robustness, which makes DAP able to deal with Level 4 uncertainty, in comparison to other approaches that are based on responding to a single or small set of hypothesized futures to achieve static robustness. The monitoring program consists of signposts and triggers. *Signposts* specify the types of information and variables that should be monitored to show (1) whether the basic plan is achieving its goals, and/or (2) whether the vulnerabilities and opportunities identified in Step 3 are impeding the plan from achieving its goals. *Triggers* are the critical signpost levels or events that, when they occur, signify that actions should be taken to ensure the basic plan remains on course to achieve its specified goals.

**Step V (Preparing the Trigger Responses)**

A series of trigger-event actions are developed prior to implementation to allow the plan to adapt to new conditions if a trigger-event occurs over the life of the plan. Preparation of these actions may include carrying out studies, engineering design work, or developing supporting political and financial plans. The results of these efforts are then saved for use if trigger events occur after the actions in Steps II and III have been implemented. Walker et al. (2013b) describe the four types of adaptive trigger-event actions that can be taken:

- **Defensive actions (DA)** – Actions taken *after initial implementation* to clarify the plan, preserve its benefits, or meet outside challenges in response to specific triggers, but that leave the basic plan unchanged.
- **Corrective actions (CR)** – Adjustments to the basic plan in response to specific triggers.
- **Capitalizing actions (CP)** – Actions taken *after initial implementation* to take advantage of opportunities that further improve the performance of the basic plan.
- **Reassessment (RE)** – A process initiated when the analysis and assumptions critical to the plan's success have lost validity (i.e., when unforeseen events cause a shift in the fundamental goals, objectives, and assumptions underlying the basic plan).

**DAP Implementation and Adaptation**

The dynamic adaptive plan is then implemented. The basic plan identified in Step II is implemented; the mitigating, hedging, seizing, and shaping actions developed in Step III are taken; and the monitoring program developed in Step IV commences. If one of the signposts' trigger events occurs after implementation of the basic plan, one or more of the adaptive actions developed in Step V is executed. If the original objectives of the plan and constraints on it remain in place upon occurrence of the trigger event, then defensive or corrective actions will be taken. If the monitoring program encounters an opportunity, then capitalizing actions will be taken. If the monitoring program indicates a change that invalidates the basic plan's goals, objectives, or intended outcomes (e.g., vulnerabilities exist or evolve beyond those considered during Step III — for example, the occurrence of a 'Black Swan' event), then the adaptive plan is reassessed. Reassessment does not mean completely starting over, as the knowledge of outcomes, objectives, measures, etc., learned during the initial DAP process would accelerate the new planning process.

## 4. CONCLUSIONS

Public policies must be devised in spite of profound uncertainties about the future. When there are many plausible scenarios for the future, it may be impossible to construct any single static policy that will perform well in all of them. It is likely, however, that the uncertainties that confront planners will be resolved over the course of time by new information. Thus, policies should be adaptive ─ devised not to be optimal for a best estimate future, but robust across a range of plausible futures. Such policies should combine actions that are time urgent with those that make important commitments to shape the future and those that preserve needed flexibility for the future. DAP is an approach to policy formulation and implementation that explicitly confronts the pragmatic reality that policies will be adjusted as the world changes and as new information becomes available. The approach allows policymakers to cope with the uncertainties that confront them by creating policies that respond to changes over time and that make explicit provision for learning. The approach makes 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.

The approach has several strengths. First, it is relatively easy to understand and explain. Second, it encourages decisionmakers to think about "what if" situations and their outcomes, and to make decisions over time to adapt while maintaining flexibility with respect to making future changes. This also helps in foreseeing undesirable lock-ins or other path dependencies so that they can be avoided. Third, it makes explicit that adaptation is a dynamic process that takes place over time. It forces decisionmakers to consider changes over time, rather than at one or a few points in time, as most scenario approaches do.

The approach is the cornerstone of the Dutch climate adaptation strategy in the water domain. It was a key part of a study with respect to the Thames estuary, and it is currently being used in the development of climate adaptation strategies in New York, Bangladesh, and Vietnam.

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