Chapter 9
Uncertainty in the Framework of Policy Analysis

Warren E. Walker, Vincent A. W. J. Marchau and Jan H. Kwakkel

Main Entry: un-cer-tain-ty
Function: noun
1: *the quality or state of being uncertain**: doubt***
2: *something that is **uncertain***
Synonyms: uncertainty, doubt, dubiety, skepticism, suspicion, mistrust, *mean lack of sureness about someone or something. **Uncertainty** may range from falling short of certainty to an almost complete lack of conviction or knowledge especially about an outcome or result. **Doubt** suggests both uncertainty and inability to make a decision. **Dubiety** stresses a wavering between conclusions. **Skepticism** implies unwillingness to believe without conclusive evidence. **Suspicion** stresses lack offaith in the truth, reality, fairness, or reliability of something or someone. **Mistrust** implies a genuine doubt based upon suspicion.* [*Merriam-Webster Online Dictionary*]

9.1 Why do We Care About Uncertainty in Policy Analysis?

9.1.1 Introduction

A few elements of the above definition of uncertainty are worth highlighting. First, this definition says uncertainty is a "… a lack of conviction or knowledge especially about an outcome or result." The word conviction suggests that uncertainty is somehow related to the beliefs we hold. The word knowledge

W. E. Walker (✉) · V. A. W. J. Marchau · J. H. Kwakkel
Faculty of Technology, Policy and Management, Delft University of Technology,
P.O. Box 5015, 2600 GA, Delft, The Netherlands
e-mail: W.E.Walker@tudelft.nl

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suggests that the level of uncertainty is related to the state of our knowledge. These two elements, conviction (strength of our belief) and knowledge are essential to what we present in this chapter; we come back to them a little later.

One of the most important roles that a policy analyst plays is to provide assistance to policymakers in choosing a preferred course of action given all of the uncertainties surrounding the choice. That uncertainties exist in practically all decisionmaking situations is generally understood by most decisionmakers, as well as by the analysts providing decision support. But there is little appreciation for the fact that there are many different dimensions of uncertainty, and there is a lack of understanding about their different characteristics, relative magnitudes, and available means for dealing with them. Also, it is widely held that decisionmakers expect analysts to provide certainties, and hence dislike uncertainty in the scientific knowledge base.

Sometimes, policymakers are able to ignore uncertainties when making policies, or base them on intuition or heuristics learned over time. Sometimes, however, the magnitude of uncertainty can be so large that heuristics can no longer be used, and the potential consequences of ignoring them could be devastating. The aim of this chapter is to provide a basis for the systematic treatment of uncertainty in policy analysis in order to improve the management of uncertainty in policymaking. Understanding the various types and sources of uncertainty would help in identifying and prioritizing critical uncertainties and would make a major contribution to structuring the work in a policy analysis project. It would also help in specifying policies to be considered in the analysis and in choosing appropriate policies to be implemented.

In policy analysis, perhaps more than in other disciplines, considering uncertainty is essential. There are many reasons and arguments for considering uncertainty. These different reasons are highlighted by a few examples. The first example comes from drug policy; the second from infrastructure projects, the third from aviation policy in the Netherlands, the fourth from the current climate change debate, and the final from the recent global financial crisis.[1]

In the 1960s, a pharmaceutical company called Merrill developed a sleeping pill that when administered to pregnant women caused serious side effects, such as birth deformities. The effects of the sleeping pill on pregnant women had not been tested; in other words, the model that was used to determine that the drug was safe was incomplete. The large number of children born with serious birth defects moved governments to institute an extensive testing regime to determine that a drug is both safe and effective (Temin 1980, p. 2). Over the years this testing regime has become ever more stringent. One rationale for a government's drug regulation policy is the desire to minimize uncertainty about the effect of a drug on

[1] For a list of real world policy cases in which policymakers ignored uncertainty, acting as if the evidence was more certain than was the case, and were confronted with the consequences of their doing so, see (EEA 2001).

people—people can get ill and even die from taking a drug, and most governments want to avoid this.

In a recent book, Flyvberg et al. (2003) review the underlying analyses making the case for several megaprojects (very large infrastructure projects). The results of their study are startling. The decision to undertake a megaproject requires a detailed assessment of costs and benefits of the project. Megaprojects are extremely expensive, and governments are almost always the initiators and financers of such projects. Megaprojects also have the potential to dramatically change their surroundings. Given the large costs and potentially large consequences, governments have a responsibility to make sure that only the megaprojects whose costs exceed their benefits are undertaken. What Flyvberg et al. found was that in almost every case they reviewed, the economic and environmental costs were systematically underestimated, while the revenues and economic benefits were systematically overestimated. One could endlessly analyze the reasons for why this happened, but here we simply note that the cost and benefit estimates of these megaprojects were almost always point estimates (single numbers!), and there was little consideration of the underlying uncertainties that could make these estimates wrong.

In 1995, after a 2-year multiphased deliberative process known as "physical planning key decision Schiphol" (PKB-Schiphol), some major decisions were made by the Dutch Parliament that were intended to guide the growth of civil aviation in the Netherlands to the year 2015. One of the outcomes of the PKB-Schiphol process was the decision to constrain the number of passengers at Schiphol to no more than 44 million passengers per year. This constraint was supposed to be more than enough to accommodate the most optimistic estimates of passenger growth until at least the year 2015. This limit was actually reached in 2004. And the noise limits, also expected to be reached no sooner than 2015, were reached in 1999.

How did such a long, costly, and deliberate planning process do such a poor job in forecasting the growth in air traffic at Schiphol? The passenger and noise projections were based on passenger forecasts that were produced by a model developed by the Central Planning Bureau (Centraal Planbureau 1992). This model assumes that the number of passengers passing through Schiphol is directly related to the value of the Netherlands' Gross National Product (GNP). This assumption was based upon the fact that, up until the time the model was built, there had been a very close relationship between the GNP and the number of passengers passing through Schiphol. Of course, no one knows with certainty what the GNP will be in 2015. So, the CPB developed three scenarios, each with a different value of GNP, which were then used to produce three forecasts of the number of passengers at Schiphol in 2015. The 44 million figure corresponds to the forecast based on the highest GNP growth rate of the three scenarios. The actual growth of GNP through 1999 was closest to the assumptions in the *low-growth* scenario. Nonetheless, (as shown in Fig. 9.1) the growth in the number of passengers during this period was significantly more than what was forecasted using the assumptions from the *high-growth* scenario—called Balanced Growth.

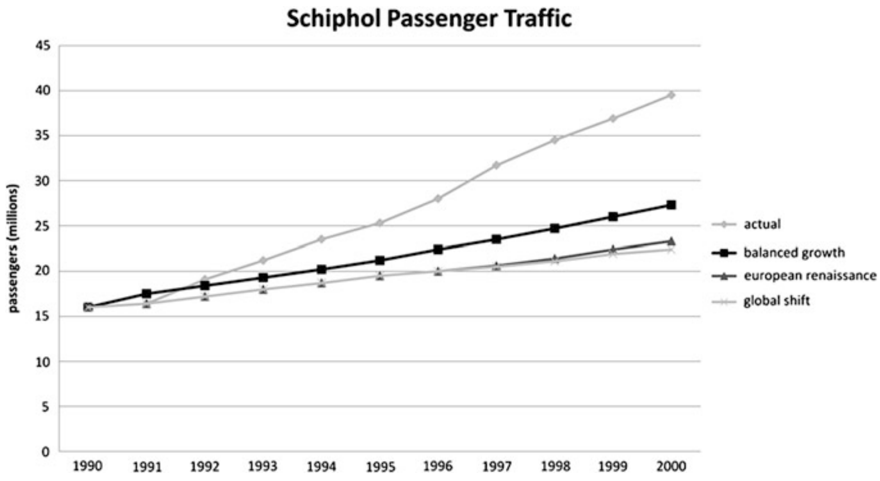


Fig. 9.1 Actual and projected growth of passenger traffic at Schiphol Airport (1990–2000)

What happened was that a number of trend breaks—unanticipated changes in the world of civil aviation—occurred after the forecasts had been made. The forecasts had assumed that the future would be a continuation of the past. But, in fact, three factors having little to do with GNP growth rates were responsible for the rapid growth of air traffic at Schiphol:

- The growth of hub-and-spoke networks, with Schiphol becoming a hub airport for KLM, where it cross-connects transfer passengers whose destination is not Amsterdam, but some other KLM city. Most of the growth in passenger traffic through Schiphol came from an increase in the number of transfer passengers carried by KLM. (The transfer traffic at Schiphol grew from 27 % in 1990 to 43 % in 1998)
- A code-sharing alliance between KLM and Northwest Airlines, which fed Northwest's European traffic through KLM, and therefore through Schiphol.
- The European Union's decision to liberalize the air transport industry—to reduce national monopolies and increase competition among airlines. As a result of this decision, European airlines began to face competitive pressures that they did not have to face in the past, fares fell, and the demand for air travel increased.

As a result, policymakers were forced to revisit their air transport policy (something they thought they would not have to do until 2015).

Another example of why uncertainty matters is climate change. Climate change research is plagued by imperfect and incomplete understanding about the functioning of natural (environmental) phenomena and processes, about how changes in these phenomena and processes translate into increases in global temperatures, and the economic and social consequences of such an increase in temperature. For a long time, the presence of these uncertainties allowed the very existence of global climate change to be denied. Now, the uncertainty as to whether climate change is taking place has been largely removed (Stern 2006). There is, however, considerable uncertainty about:

- The magnitude of climate change (there are a whole range of future scenarios that describe very different increases in average temperatures);
- The speed of climate change (which determines how quickly policy actions need to be taken);
- What this means for specific areas and regions (the effects of climate change are potentially larger for countries like Bangladesh and the Netherlands than for countries like Mongolia);
- What should be done to mitigate climate change and its adverse consequences (because there is a lack of knowledge about the costs and benefits of different alternatives for protecting ourselves from the adverse consequences of climate change).

A final example of why acknowledging uncertainty and dealing with it is of great importance is the experience of the financial crisis that gripped the world in 2008–2009. The speed and the severity of the decline in world economies was unprecedented, but policymakers did not see it coming and were unprepared to deal with it. As Alan Greenspan admitted (Committee Hearings of the US House of Representatives 2008): "I found a flaw in the model that I perceived is the critical functioning structure that defines how the world works… I was shocked, because I had been going for 40 years or more with very considerable evidence that it was working exceptionally well."

The above examples have suggested why we believe that considering uncertainty is essential in a policy analysis. First, it should be clear that uncertainty is at the heart of the very nature of policy analysis. The objective of policy analysis is to help policymakers make decisions about the future—decisions that affect (positively or negatively) people. The future is impossible to predict. But, that is no reason to throw up one's hands and decide to ignore uncertainty. Quite the opposite. Ignoring uncertainty could lead to large adverse consequences for people, countries, and the Earth, and policymakers have an interest in minimizing the possibility of such adverse consequences happening.

So, it is important for policy analysts and policymakers to accept, understand, and manage uncertainty, since:

- given the lack of crystal balls, uncertainties about the future cannot be eliminated;
- ignoring uncertainty can result in poor policies, missed chances and opportunities, and lead to inefficient use of resources; and
- 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.

The remainder of this chapter is divided into five sections. Section 9.2 introduces the framework for policy analysis that is used to define and specify different types of uncertainty. Based on this framework, different ways of dealing with uncertainty in conducting a policy analysis are discussed in Sect. 9.3. While a variety of approaches are mentioned, the section focuses on ways to address what is called 'deep uncertainty'. Section 9.4 provides an in-depth treatment of one of these approaches—the use of flexible, adaptive policies. Section 9.5 provides a summary and some conclusions.

9.2 What is Uncertainty?

9.2.1 Defining Uncertainty

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), and Smithson (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 policymaker (and the various actors involved in the policymaking process).

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 our understanding is more limited or that the processes are more complex than we 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).

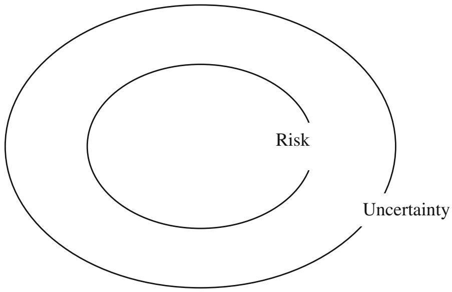


Fig. 9.2 Risk and uncertainty

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 made 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).

Knight saw risk and uncertainty as being disjoint—with risk being calculated as the probability of an event times the loss if the event occurred. We prefer to treat risk as one kind of uncertainty—a low level of uncertainty, that can be quantified by using losses and probabilities. The remaining uncertainties are 'deeper', and do not have probabilities associated with them. That is, uncertainty is a broader concept than risk (see Fig. 9.2).

Formally, as defined by Walker et al. (2003), we will consider uncertainty to be "*any departure from the (unachievable) ideal of complete determinism*." Or, in mathematical terms:

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

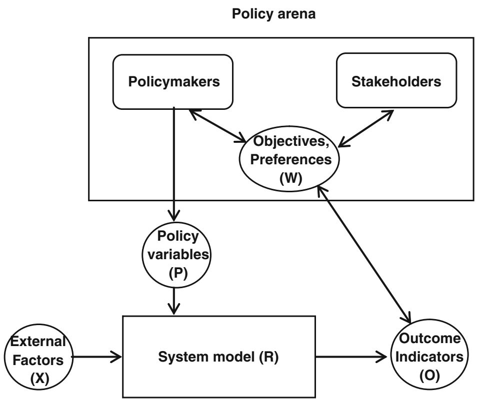


Fig. 9.3 Framework for model-based policy analysis

9.2.2 The Dimensions of Uncertainty in Policy Analysis

To aid in the decisionmaking process, policy analysts assess the outcomes of alternative policies. As described in previous chapters and as detailed by Walker (2000a), a common approach to rational-style policy analysis is to create a model of the system of interest that defines the boundaries of the system and describes its structure and operations—i.e., the elements, and the links, flows, and relationships among these elements. In this case, the analysis is referred to as being model-based. The system model is usually, but not necessarily, a computer model. This chapter is all about uncertainty in model-based policy analysis.

As described in previous chapters and in the introduction to Part II, the traditional policy analysis approach is built around an integral system description of a policy field (see Figs. II.2 and II.3; Fig. 9.3 is basically Fig. II.2 with capital letters added to identify some of the elements that will be referred to below.) At the heart of this view is the *system* comprising the policy domain, defined by distinguishing its component elements (or subsystems) and their mutual interrelationships (R). The system model represents the cause–effect relationships characterizing the system. In a mathematical model, the relationships among the various components of the system are expressed as functions. A computer model is a translation of the mathematical model into computer code. As explained in Chap. 7, the resulting system model generally represents a compromise between desired functionality, plausibility, and tractability, given the resources at hand (data, time, money, expertise, etc.).

The results of these interactions (the system outputs) are called *outcomes of interest* (O) and refer to the characteristics of the system that are considered relevant criteria for the evaluation of policies. The *valuation of outcomes* refers to the (relative) importance given to the outcomes by crucial stakeholders, including policymakers, reflecting their goals, objectives, and preferences. These involve the tradeoffs stakeholders make among the different outcomes of interest and are often represented by giving weights (W) to the outcomes of interest. In case there is a gap between (some of) the system outcomes and the goals, *policies* (P) are implemented to influence the behavior of the system in order to help to achieve the goals. If policies were the only forces affecting the system we would have a 'closed loop' system, based upon which the policymakers and stakeholders could fully control the system in order to reach their desired goals. However, in reality, there are also *external forces* (X) influencing the system. External forces refer to forces that are not controllable by the policymakers or stakeholders but may influence the system significantly (e.g., technological developments, demographic developments, economic developments). As such, both policies and external forces are developments outside the system that can affect the structure of the system and, hence, the outcomes of interest to policymakers and other stakeholders.

In policy analysis, the following basic questions are addressed:

- What is the effect of external forces on the system? (So, what will the future system look like, without new policies?):

$$R_1 = f_1(X, R) \text{ (Reference case)}$$

- What is the effect of policy measures on the future system?:

$$R_2 = f_2(P, R_1) \text{ (Policy cases)}$$

- What is the effect of changes in the system on the outcomes of interest?:

$$O_1 = f_3(R_1); \; O_2 = f_4(R_2)$$

Based on the policy analysis framework, a classification of uncertainties with respect to policymaking can be made. Such a classification has been developed by Walker et al. (2003). Their classification has two fundamental dimensions:

- *Location*: where the uncertainty manifests itself within the policy analysis framework.
- *Level*: the magnitude of the uncertainty, ranging from deterministic knowledge to total ignorance.

This produces a 2D matrix of uncertainty types. Uncertainty can manifest itself in several locations (specifically, in the external factors (X), the system (R), and the weights (W)). And the uncertainty found at each location can be any one of the levels. The following two subsections discuss the uncertainties in these two dimensions.

The explanation of uncertainty within each cell of this matrix can be distinguished by what Walker et al. call its *nature*. The nature of an uncertainty can be due to the imperfection of our knowledge (also called *epistemic* uncertainty) or to the inherent variability of the phenomena being described (also called *aleatoric* or *ontic* uncertainty). Dewulf et al. (2005) add a third nature of uncertainty:

ambiguity, which is defined as '….*the simultaneous presence of multiple equally valid frames of knowledge*'. Uncertainty about whether a Las Vegas hotel will collapse due to a structural defect is an epistemic uncertainty; uncertainty about the next poker hand to be dealt in a specific game in a Las Vegas casino is an aleatoric uncertainty; ambiguity arises when there are many interpretations of a situation (e.g., by different stakeholders). In the epistemic case, the uncertainty can be reduced (by collecting more information, or by waiting until the future becomes known). In the aleatoric case, some uncertainty must remain (although in some cases it can be reduced by additional observations and/or experiments). Aleatoric uncertainty in model-based policy analysis can be handled through use of the traditional tools of probability and statistics, for which there are many books.[2] Ambiguity has been partially addressed in the chapters dealing with the policy process (Chap. 6) and actor models (Chap. 8). It will also be addressed in this chapter in the discussion about uncertainty about the appropriate system model. So, in the remainder of this section we focus on the location and level dimensions of uncertainty, and assume that we are dealing with epistemic uncertainty.

9.2.3 The Location of Uncertainty

In terms of the policy analysis framework of Fig. 9.3, one can identify four primary locations of uncertainty that affect the choice of an appropriate policy:

(1) *uncertainty about the external factors* (X);
(2) *uncertainty about the system response to the external factors and/or policy changes* (R);
(3) uncertainty in locations (1) and (2) combine to produce *uncertainty about the system outcomes* (O) or, in the case of model-based decision support, *model outcome uncertainty*;
(4) *uncertainty about the relative importance placed on the outcomes by the participants in the policymaking process* (their weights (W) or valuation of the outcomes).

These four locations of uncertainty are highlighted in Fig. 9.4 and are discussed in more detail below.

Model outcome uncertainty is sometimes called *prediction error,* since it is the discrepancy between the true value of an outcome and the model's predicted value. If the true values are known (which is rare, even for scientific models), a formal validation exercise can be carried out to compare the true and predicted values in order to establish the prediction error. However, practically all policy analysis models are used to extrapolate beyond known situations to estimate outcomes for situations that do not yet exist. For example, the model may be used to explore

[2] One of the best of such book is (Morgan and Henrion 1990)

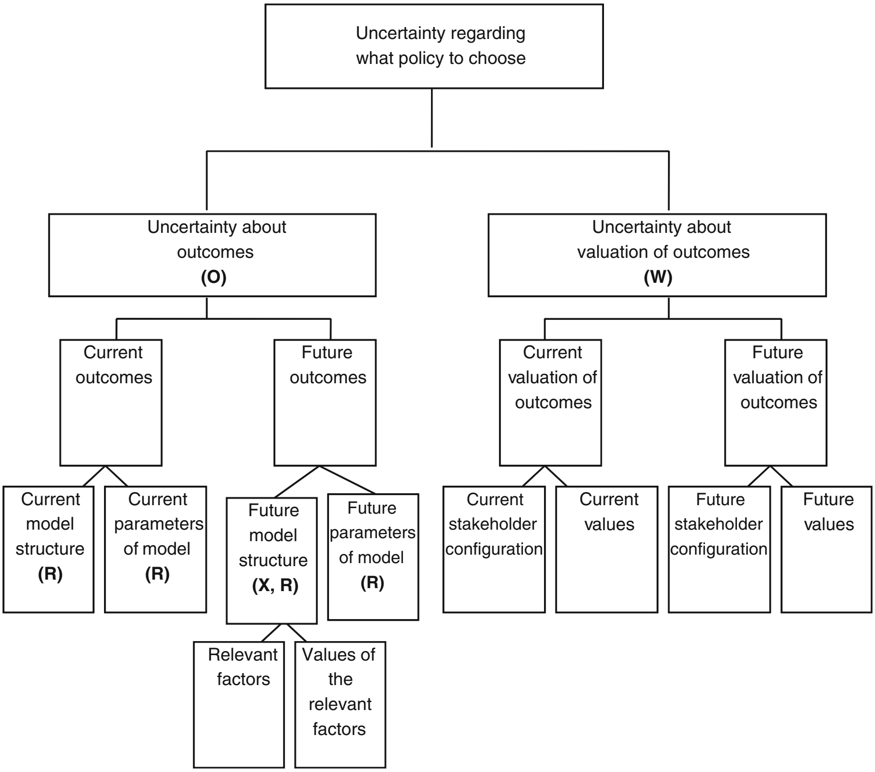


Fig. 9.4 Uncertainty locations

how a policy would perform in the future or in several different futures. In this case, in order for the model to be useful in practice, it is necessary to (1) build the credibility of the model with its users and with consumers of its results [see, for example, (Bankes 1993)], and (2) describe the uncertainty in the model outcomes (e.g., using a typology of uncertainties such as that presented in (Walker et al. 2003)). (Issues surrounding system model validation are discussed in more detail in Chap. 7). Model outcome uncertainty is the accumulated uncertainty caused by the uncertainties in the locations *external factors* and *system domain for policies* that are propagated through a model and are reflected in the resulting estimates of the outcomes of interest.

There are two major sources of model outcome uncertainty: (1) uncertainty about the external factors (X), and (2) uncertainties about the new system (and, therefore, the system model) that results from these external factors (R). Uncertainty about the *external factors* that are not under the control of the policymakers and that produce changes within the system (the relevant scenario variables) are of particular importance to policy analyses, especially if they are likely to produce large changes in the outcomes of interest.

Not only is there often great uncertainty in the external factors and their magnitudes, there is also often great uncertainty in the *system response* to these factors. There are two major categories of uncertainty within this location of uncertainty: (1) *model structure* uncertainty, and (2) *parameter* uncertainty. *Model structure uncertainty* arises from a lack of sufficient understanding of the system (past, present, or future) that is the subject of the policy analysis, including the behavior of the system and the interrelationships among its elements. Uncertainty about the structure of the system that we are trying to model implies that any one of several model formulations might be a plausible representation of the system, or that none of the proposed system models is an adequate representation of the real system. We may be uncertain about the current behavior of a system, the future evolution of the system, or both. Model structure uncertainty involves uncertainty associated with the relationships between inputs and variables, among variables, and between variables and output, and pertains to the system boundary, functional forms, definitions of variables and parameters, equations, assumptions, and mathematical algorithms.

Parameters are constants in the model, supposedly invariant within the chosen context and scenario. There are the following types of parameters:

- *Exact parameters,* which are universal constants, such as π and e.
- *Fixed parameters,* which are parameters that are so well determined by previous investigations that they can be considered exact (e.g., the acceleration of gravity (g)).
- A priori *chosen parameters,* which are parameters that may be difficult to identify by calibration and are chosen to be fixed to a certain value that is considered invariant. However, the values of such parameters are associated with uncertainty that must be estimated on the basis of *a priori* experience or by expert judgment.
- *Calibrated parameters,* which are parameters that are essentially unknown from previous investigations or that cannot be transferred from previous investigations due to lack of similarity of circumstances. They must be determined by calibration, which is performed by comparison of model outcomes for historical data series regarding both input and outcome. The parameters are generally chosen to minimize the difference between model outcomes and measured data on the same outcomes.

One of the best treatments of uncertainty about system model uncertainty and how to deal with it is given in (Morgan and Henrion 1990, Chap. 8, which is entitled "The propagation and analysis of uncertainty"). It has also been touched upon in Chap. 7 of this book. In terms of location, this chapter will focus on uncertainty in the external factors, the system response to these factors, and how to deal with these in making policies.

The third location of uncertainty in model-based policy analysis refers to the *valuation of outcomes*: i.e., the (relative) importance given to the outcomes by policymakers and crucial stakeholders (the weights). One can distinguish uncertainty about the *current stakeholders' configuration and their current values* as well as the *future stakeholders' configuration and their future values.* Even if the people who are affected by a policy are clear, there might still be uncertainty about how each of these stakeholders currently value the results of the changes in the system. The uncertainty about current values is related to different perceptions, preferences, and choices the system's stakeholders currently have regarding outcomes. And, even if the outcomes are known and there is no uncertainty about the current stakeholders' configuration and their valuation of outcomes, in time, new stakeholders might emerge and the values of the current stakeholders may change over time in unpredictable ways, leading to different valuations of future outcomes than those made in the present. For instance, the occurrence of a specific event (e.g., disaster), unexpected cost increases (e.g., in the price of oil), or new technologies (e.g., mobile telephony) can lead to changes in values. These changes in values can affect policy decisions in substantial ways.

9.2.4 The Level of Uncertainty

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. The range of levels of uncertainty, and their challenge to decisionmakers, was acknowledged by Donald Rumsfeld, who famously said:

> As we know, there are known knowns—these are things we know we know. We also know there are known unknowns—that is to say we know there are some things we do not know; but there are also unknown unknowns—the ones we don't know we don't know…. It is the latter category that tends to be the difficult one.[3]

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 several intermediate levels (e.g., Courtney 2001; Walker et al. 2003; Makridakis et al. 2009; Kwakkel et al. 2010b). We define five intermediate levels. In Fig. 9.5, the intermediate levels are defined with respect to the knowledge assumed about the four locations of uncertainty: (a) the future world (X), (b) the model of the relevant system for that future world (R), (c) the outcomes from the system (O), and (d) the weights that the various stakeholders will put on the outcomes (W). The levels of uncertainty are briefly discussed below.

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 (Hillier and Lieberman 2001, p. 43). Level 1

[3] Donald Rumsfeld, Department of Defense news briefing, Feb. 12, 2002.

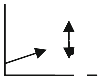
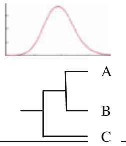
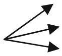
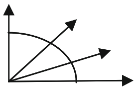
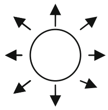
		Level 1	Level 2	Level 3	Level 4	Level 5	
Complete Certainty	**Context**	A clear enough future (with sensitivity) 	Alternate futures (with probabilities) 	Alternate futures (with ranking) 	A multiplicity of plausible futures (unranked) 	Unknown future 	Total ignorance
	System model	A single system model	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	
	System outcomes	Point estimates with sensitivity	Several sets of point estimates with confidence intervals	Several sets of point estimates, ranked according to their perceived likelihood	A known range of outcomes	Unknown outcomes; know we don't know	
	Weights on outcomes	A single set of 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	

Fig. 9.5 The progressive transition of levels of uncertainty from complete certainty to total ignorance

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 alternative futures, 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 external factors (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 5 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). 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.

9.3 Policymaking in the Face of Uncertainty About the Future

Sounds super nice, but not practical at all.

High quality does not require the elimination of uncertainty, but rather its effective management… *The objective of uncertainty management is to make sure the users of information can assess its strength relevant to their purposes.*

(*Funtowicz and Ravetz* 1990, p.1)

In most real world policymaking situations, decisions must be taken in spite of there being uncertainty about the future situation, about the outcomes from the decision, and about the future valuation of the outcomes. Here, decisionmaking is faced with the prospect of surprise—and the failure of policies that are based on assumptions that do not come to pass. It is in this gray area between the well known and what is not known that the location, level, and nature of uncertainty ought to affect the approach to decisionmaking. The ultimate goal of decision-making in the face of uncertainty should be to reduce the undesirable effects of negative surprises, rather than hoping or expecting to eliminate them, and to take advantage of positive surprises (Dewar 2002; McDaniel and Driebe 2005).

There are a variety of methods and tools that have been developed for dealing with uncertainty in conducting a model-based policy analysis study, such as the use of sensitivity analysis, probabilities, statistics, Monte Carlo simulation, scenarios, etc. These are not general purpose tools, but are useful for dealing with specific types of uncertainty in specific types of situations. One step in a policy analysis study should be an analysis of the uncertainties that the study will have to deal with. The typology presented in Sect. 9.2 can be used to provide a structured way of identifying these uncertainties. Once these uncertainties have been identified, the appropriate tools can be selected to deal with them.

Most of the quantitative analytical approaches deal with Level 1 and Level 2 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 everincreasing 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, or deeper, levels of uncertainty (i.e., Levels 3, 4, and 5). These uncertainties 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 higher 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. Many of the negative consequences from policy decisions described in Sect. 9.1.1 were due to the use of approaches that did not take into account the fact that they were facing conditions of Level 3 and higher uncertainty. New policy analysis approaches are needed to deal with these conditions.

We refer to Level 4 and Level 5 uncertainties as 'deep uncertainty'. 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." The 'do not know' portion of the definition applies to Level 5 uncertainties, and the 'cannot agree upon' portion of the definition applies to Level 4 uncertainties.

In this section, we first summarize traditional ways of dealing with uncertainty about the future in conducting a policy analysis study, including when they are appropriate and when they are not. We then devote the remainder of the chapter to ways of dealing with deep uncertainty.

The most common approaches for addressing these five levels of uncertainty are:

Level 1: Assume that the future is clear and base the policy on that assumption or on a single forecast. In this case, it is possible to use a single (perhaps, optimization) model to find the 'best' policy. Sensitivity analysis on the model's parameters can be used to explore how sensitive the policy results are to the assumptions about the future. This is sometimes called the 'predict-and-act' approach. The resulting policy is 'optimal', but is fragilely dependent on the underlying assumptions. This approach works best when dealing with Level 1 uncertainties.

Level 2: Assume that there are a few alternative futures that can be predicted well enough (and to which probabilities can be assigned). In this case, a model for each future can be used to estimate the outcomes of policies for these futures, or a decision tree can be constructed based on the probabilities. A preferred policy can be chosen based on the outcomes and the associated probabilities of the futures (i.e., based on 'expected outcomes' and levels of acceptable risk). These approaches work best when dealing with Level 2 uncertainties.

Level 3: There are no analytic methods directly tailored for treating Level 3 uncertainties. Typically, one tries to reduce a Level 3 uncertainty to a Level 2 uncertainty by assigning probabilities to the ranked likelihoods, or by treating all the possibilities as equal (i.e., increasing it to a Level 4 uncertainty). Conceptually, a Level 3 approach would be to identify a policy that will perform well in the most likely futures, and does not perform too poorly in the less likely futures.

Level 4: Identify a policy that is robust (i.e., works fairly well) across a range of plausible futures. This approach assumes that, although the likelihood of the future worlds is unknown, the plausible futures can be specified well enough to identify a (static) policy that will produce acceptable outcomes in most of them. We call this *static robustness*; it is more often called *scenario planning* (van der Heijden 1996). It works best when dealing with Level 4 uncertainties.

Level 5: Broadly speaking, although there are differences in definitions, and ambiguities in meanings, the literature offers three (overlapping, not mutually exclusive) ways for dealing with Level 5 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
- *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 approach appears to be the most robust and efficacious way of dealing with Level 5 uncertainties (Kwakkel et al. 2012).

We discuss the approaches identified above for the various levels of uncertainty in the following subsections. The first two are discussed fairly briefly, since they are well documented elsewhere. Given the lack of analytic approaches for Level 3 uncertainty, and a tendency to either treat it using Level 2 or Level 4 approaches, we do not discuss Level 3 in any more detail. We discuss Level 4 (scenario planning/static robustness) and Level 5 (adaptive robustness) approaches more extensively, since they are less well documented.

9.3.1 The Predict-and-Act Approach

As mentioned in Chap. 2, and described in more detail by Walker and Fisher (2001), policy analysis developed out of operations research and systems analysis. These disciplines generally study real world operational systems in order to develop "an overall understanding of optimal solutions to executive type problems" (Churchman et al. 1957, p. 7). They have to deal with Level 1 uncertainties, and, therefore, can apply a "predict-and-act" approach. The approach, however, is not generally useful for handling policy analysis problems.

Applying the 'predict-and act' paradigm to a policy analysis problem would include building a model of the system of interest in order to estimate the outcomes of alternative policies, assuming some future world. (The model might be a stochastic model if there were stochastic uncertainties.) The outcomes for different policies would then be valued using some form of cost–benefit analysis, multi-criteria analysis, or optimization technique in order to end up with a 'best' policy.

The usual approach for handling uncertainty in the predict-and-act approach is by means of sensitivity analysis—varying the assumptions and observing how the results would change (Saltelli et al. 2000).

This approach can work reasonably well for policy problems with a short planning horizon in which the system is reasonably stable. Within a narrow time frame, the range of possible futures is somewhat constrained, and it is possible to determine, within reasonable error bands, important policy-exogenous and policy-dependent events.

However, as the planning horizon stretches toward the distant future, the nature of the policy problem changes in a major qualitative manner. The "fan" of possible futures expands [Rosenhead (1989) calls this the "trumpet of uncertainty"], so that not only is prediction with certainty not possible, but even "coming close" is not attainable. Put in formal terms, the sensitivity of any predictions is so large that results from a best estimate model are not credible.

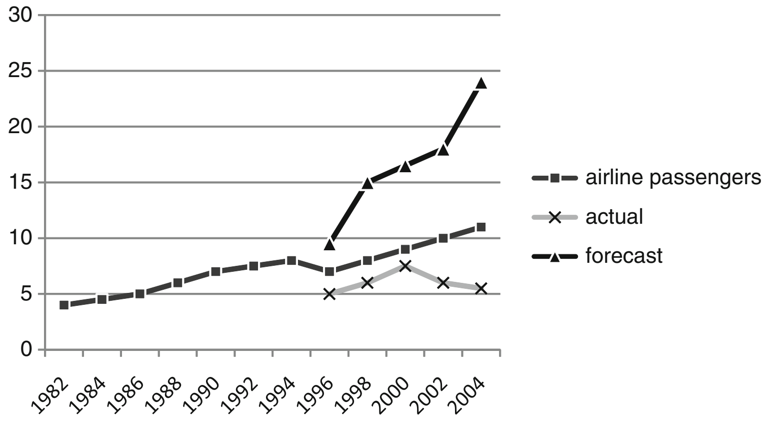


Fig. 9.6 Eurostar passengers: forecast and actual

Selecting policies on the basis of a maximum likelihood future means betting on a future that, although the most likely among the candidates proffered, still is almost certain not to occur. And the policy that works best for the maximum likelihood future may not work very well for many of the futures that could occur, whose collective likelihoods are non-negligible.

Quade (1989) uses the following example to warn policy analysts against basing a policy on a single set of best guesses about the future world:

> [S]uppose there is uncertainty about 10 factors and we make a best guess for all 10. If the probability that each best guess is right is 0.6 (a very high batting average for most best guesses), the probability that all 10 are right is about six-tenths of 1 %. If we confined the analysis to this one case, we would be ignoring a set of possibilities that had something like 99.4 % probability of occurring.

In this approach, the implicit assumption underlying the forecasts is generally that the future will look significantly like the past; the future world will be structurally more or less the same as the current world—perhaps more populated, richer, dirtier—but, essentially the same. Unfortunately, there is no particular reason why the future should look like the past. By assuming it does, we do not solve the uncertainty problem, we merely sweep it under the rug, often with serious consequences.

For example, the competition from low-cost air carriers and price reactions of ferries were not taken into account in planning for the railroad tunnel under the English Channel (see Fig. 9.6). This resulted in a significant overestimation of the tunnel's revenues and market position, with devastating consequences for the project.

9.3.2 The Expected Outcomes Approach

In this approach, policymakers make policy choices based on an assumption that the probabilities of different futures are known. In particular, several forecasts of the future are made, probabilities are assigned to the futures, and alternatives are evaluated based on their expected (probability-weighted) performance and/or ‘confidence intervals’ around the predicted outcomes. Not only may the futures be known probabilistically, but the other uncertainties (e.g., parametric uncertainty in the system model) may also be known probabilistically.

Referring to Fig. 9.3, if probabilities can be assigned to the scenarios (X), the system model and/or the parameters of the model (R), and/or the stochastic variables in the model, then probabilities can be assigned to the outcomes of interest (O) [see (Morgan and Henrion 1990), Chap. 8: “The propagation and analysis of uncertainty”]. In this case, policymakers and other stakeholders will be able to choose a preferred policy based upon the resulting outcomes and their probabilities. There are many methods that have been developed for doing so. Most of these are based upon the various policies’ expected (probability-weighted) performance. In these cases, the preferred policy is usually chosen in a way that is similar to the way a policy is chosen in the predict-and-act approach—e.g., the one that has the highest weighted (using weights W) expected outcomes. Also, a cost–benefit analysis can be performed, using expected costs and expected benefits. The probability distribution of the outcomes can be used to place confidence intervals around the expected values. To take into account the dynamics of the effects of a policy and the time value of money, the Net Present Value (NPV) of the expected benefits minus the expected costs is often calculated. It discounts all future cash flows to their present value. However, as uncertainty increases, it becomes impossible to forecast future cash flows and their timing with any degree of confidence or to arrive at an appropriate discount rate.

An approach that uses these probabilities more directly in the analysis is Decision Analysis (DA) [see, for example, (Keeney and Raiffa 1976) and (Clemen 1996)]. DA commonly uses a graphical representation, such as a causal diagram or decision tree, to represent the alternatives available to a decisionmaker, the uncertainty being faced, and the resulting outcomes. Uncertainties are represented through probabilities (e.g., at the various branch points in the decision tree). A policy is valued by assigning weights to the various outcomes and choosing the policy that produces the best expected result (i.e., the ‘maximum utility’).

Another somewhat related approach is called Real Options Analysis (ROA) [Amram and Kulatilaka (1999); Trigeorgis (2000); Kodukula and Papudesu (2006)]. It is conceptually similar to DA, but is more narrowly focused on multi-stage, dynamic problems involving infrastructure planning or capital budgeting. Also, it takes into account uncertainty about the future evolution of the factors that determine the value of the project, and the decisionmaker’s ability to respond to the evolution of these factors. The reason that it is called ‘real options’ is that it applies the concepts related to financial ‘put’ and ‘call’ options to infrastructure planning/capital budgeting decisions (so, 'real property' rather than 'financial instruments'). In finance, a financial option conveys the right, but not the obligation, to engage in a future transaction (e.g., the right to buy or sell stock within a predetermined period at a predetermined price). The value of a financial option reflects the stock's expected value development, including any uncertainties that surround this expectation. In other words, the value of a financial option can be seen as the price to be paid to reduce uncertainty and increase flexibility. The application of the same approach for valuing options involving real assets is called ROA. A real option is, therefore, the option to make or abandon a capital investment—e.g., the opportunity for an electricity utility to expand a power plant if the conditions are right.

As mentioned above, ROA enables the valuation of flexibility. The framework of options thinking recognizes that uncertainty adds value to options; i.e., uncertainty is a driver of value and can be viewed as a positive element. If NPV is the Net Present Value of an investment (this where the probabilities are applied), the value of flexibility (i.e., the value of the option) can be given as (Trigeorgis 2000):

Flexibility value = NPV (with flexibility)−NPV (without flexibility)

This formula entails the comparison of NPV between a project with an option and without one.

Another important aspect is that having an option comes at a cost. For example, creating a real option by over dimensioning an infrastructure project requires an extra investment cost (e.g., costs of building extra capacity to a power plant). As a general rule, under ROA, an option should be chosen as long as the benefits from the flexibility are greater than the costs of creating it.

Agusdinata (2008) provides an example of ROA applied to a power plant investment decision (to illustrate an option of initially building a power plant with more production capacity than necessary in order to be able to gain more profits if the circumstances change in the future). De Neufville (2003) illustrates the wide range of applications for ROA using cases from many fields of engineering.

9.3.3 Using Scenarios to Deal with Level 4 Uncertainty: The Traditional Scenario Planning Approach

When faced with Level 4 uncertainties, in which the predict-and-act approach and expected value approaches are not appropriate, policy analysts will generally use scenario planning. The core of this approach is that the future can be specified well enough to identify policies that will produce favorable outcomes in one or more specific plausible future worlds. The future worlds are called scenarios. {Börjeson et al. (2006) call these 'explorative scenarios' to differentiate them from 'predictive scenarios', which can be used to deal with Level 1 and Level 2 uncertainties, and 'normative scenarios', which use backcasting [see, for example, Quist (2007)] to determine how a specific desired target can be reached}. The use of the term *scenario* as an analytical tool dates from the early 1960s, when researchers at the RAND

Corporation defined states of the world within which alternative weapons systems or military strategies would have to perform. Since then, their use has grown rapidly, and the meanings and uses of scenarios have become increasingly varied. Here, we use Quade's (1989) definition: "A description of the conditions under which the system or policy to be designed, tested, or evaluated is assumed to perform".

Scenarios are "stories" of possible futures, based upon logical, consistent sets of assumptions, and fleshed out in sufficient detail to provide a useful context for engaging planners and stakeholders. A scenario in scenario planning includes assumptions about developments within the system being studied and developments outside the system that affect the system, but exclude the policy options to be examined. Because the only sure thing about a future scenario is that it will not be exactly what happens, several scenarios, spanning a range of developments, are constructed to span a range of futures of interest. No probabilities are attached to the futures represented by each of the scenarios. They have a qualitative function, not a quantitative function. Scenarios do not tell us what will happen in the future; rather they tell us what can (plausibly) happen. They are used in scenario planning to prepare for the future: to identify possible future problems, and to identify robust (static) policies for dealing with the problems.

Similar to the predict-and-act approach, in scenario planning policy analysts use best estimate models (based on the most up-to-date scientific knowledge) to examine the consequences that would follow from the implementation of each of several possible policies. But, in this case, they do this 'impact assessment' for each of the scenarios. The 'best' policy is the one that produces the most favorable outcomes across the scenarios. [Such a policy is called a *robust* (static) policy.]

There is no general theory that allows us to assess scenario adequacy or quality. There are, however, a number of criteria that are often mentioned in the literature as being important. Schwarz (1988) gives a brief summary of them. The most important of these are consistency, plausibility, credibility, and relevance.

- Consistency: the assumptions made are not self-contradictory; a sequence of events could be constructed leading from the present world to the future world;
- Plausibility: the posited chain of events *can* happen;
- Credibility: each change in the chain can be explained (causality);
- Relevance: changes in the values of each of the scenario variables is likely to have a large effect on at least one outcome of interest.

A structured process for developing scenarios consisting of a number of explicit steps has been used in several policy analysis studies. The steps, summarized by Thissen (1999), and based on the more detailed specifications of RAND Europe (1997), Schwartz (1996), and van der Heijden et al. (2002), are:

Step 1. Specify the system, its outcomes of interest, and the relevant time horizon. A *system diagram* can be used to identify what is considered inside and outside the system, the system elements that affect or influence the outcomes of interest, and their interrelationships.

	Change would lead to a low impact (for all outcomes of interest)	Change would lead to a **high impact** (on at least one outcome of interest)
Factor/change is **uncertain**	These factors/changes can be included (for 'color') or left out of the scenarios	**These factors/changes are candidates for scenarios**
Factor/change is fairly certain	These factors/changes can be included (for 'color') or left out of the scenarios	These factors/changes are included in all the scenarios as "autonomous developments"

Fig. 9.7 Selecting relevant factors/system changes for scenarios

Step 2. Identify external factors (X) driving changes in the system (R) (and, thereby producing changes in the outcomes of interest (O)). Whether or not a particular external factor is relevant depends on the magnitude of the change in the system and its implications for the outcomes of interest. There are many judgments involved in defining the system under consideration, the relationships among the subsystems, and the definition of what is relevant. Thus, the determination of relevant factors and changes is necessarily subjective. Potentially relevant factors and changes are often best identified by conducting a series of interactive brainstorming or focus group sessions involving experts and/or stakeholders.

Step 3. Categorize factors and resulting system changes as fairly certain or uncertain. The factors/system changes from Step 2 are placed into one of two categories—fairly certain or uncertain (see Fig. 9.7). Those factors/system changes about which we are fairly certain are placed into this category. The remaining factors/changes are placed into the uncertain category. The factors/system changes in the fairly certain category are included in all the scenarios. The uncertain factors/system changes are used to identify the most important and relevant uncertainties that have to be taken into account.

Step 4. Assess the relevance of the uncertain factors/system changes. The analyses should focus on the uncertain factors/system changes that have the largest effects on the outcomes of interest. To identify them, the impact of each uncertain factor/system change is considered with respect to each of the outcomes of interest. Based on the estimated impact that the resulting system change has on the outcomes of interest, the factor/system change is placed in either a high or low impact category (see Fig. 9.7).

The uncertain factors and system changes in the low impact category are dropped from further consideration. The uncertain factors and system changes in the high impact category (those that have a high impact on at least one of the outcomes of interest), along with the fairly certain elements, form the basis for the scenarios.

Step 5. Design several scenarios based on combinations of different developments in the external factors. These should provide strikingly different images of plausible futures. A brief but imaginative description of the essential characteristics of the future depicted by each of the scenarios should then be provided. Once the specific scenarios are identified, the values of the scenario variables can be used as inputs to the system model and/or the system represented by the scenario is used for the system model. This forms the basis for the subsequent assessment of policy options.

The benefits of using scenarios in policy analysis are threefold. First, it helps us to deal with situations in which there are many sources of uncertainty. Second, it allows us to examine the "what ifs" related to scenario uncertainties; it suggests ways in which the system could change in the future and allows us to examine the implications of these changes. Finally, scenarios provide a way to explore the implications of Level 4 uncertainty for policymaking (prepare for the future) by identifying possible future problems and identifying (static) robust policies for dealing with the problems.

However, from an analytic perspective the scenario approach has several problems. The first problem is deciding which future external developments to include in the scenarios. Typically, these developments are decided upon by experts (collectively and individually). However, in the face of uncertainty, no one is in a position to make this judgment. A second problem is that, even if we knew all of the relevant external factors, the values of these factors are likely to be uncertain. So, we have little idea about whether the range of futures provided by the scenarios covers all, 95 %, or some other percentage of the possible futures. Thus, even if we choose a policy that performs well in our scenarios, we do not know whether this policy will perform well in the future or not. A third problem with this approach has to do with the large range in the performance estimates generated by the scenarios. If the uncertainty included in this range is large, policymakers often tend to fall back on a single 'most likely' scenario (assuming Level 3 uncertainty), or the do-nothing approach, arguing that "we do not have sufficient information to make a decision at this time". The latter is probably the worst possible outcome—when the level of uncertainty is high, and the potential consequences are large, it would probably be better if policymakers acted rather than waited.

9.3.4 The Exploratory Modeling and Analysis Approach

An alternative scenario-related approach for Level 4 uncertainty (and for Level 5 uncertainty), which uses scenario variables in a different way, is the Exploratory Modeling and Analysis (EMA) approach (Agusdinata 2008), which is closely related to the Robust Decisionmaking (RDM) approach (Lempert et al. 2006).

The main assumption

EMA turns the 'predict-and-act' approach on its head. It begins by acknowledging the fact that a validatable predictive policy analysis model cannot be built (see Chap. 7). It then asks the question 'in that case, what can we do with our system model?'. As noted in Sect. 9.3.1, in situations with deep uncertainty, relying on a 'best estimate' model to predict system behavior can result in the choice of a very poor policy. Therefore, rather than attempting to predict system behavior, EMA aims to analyze and reason about the system's behavior (Bankes 1993; Kwakkel et al. 2010c). Under conditions of deep uncertainty, even a model that cannot be validated can still be useful (Hodges 1991). One use is as a hypothesis generator, to get insight into possible behaviors of a system. A combination of input and system variables can be established as a hypothesis about the system. One can then ask what the system behavior would be if this hypothesis were correct.

What is that???

EMA supports this process of researching a broad range of assumptions and circumstances. In particular, EMA involves exploring a wide variety of scenarios, alternative model structures, and alternative value systems. The exploration is carried out using computational experiments. A computational experiment is a single run of a given model structure and a given parameterization of that structure. It reveals how the real world would behave if the various hypotheses presented by the structure and the parameterization were correct. By exploring a large number of these hypotheses, one can get insights into how the system would behave under a large variety of assumptions. To support the exploration of these hypotheses, data mining techniques for analysis and visualization are employed. How to cleverly select the finite sample of models and cases to examine from the large or infinite set of possibilities is one of the major issues to be addressed in any EMA application. A wide range of research strategies are possible, including structured case generation by Monte Carlo, Latin Hypercube, or factorial experimental design methods, search for extremal points of cost functions, sampling methods that search for regions of "model space" with qualitatively different behavior, or combining human insight and reasoning with formal sampling mechanisms. Computational experiments can be used to examine ranges of possible outcomes, to suggest hypotheses to explain puzzling data, to discover significant phases, classes, or thresholds among the ensemble of plausible models, or to support reasoning based upon an analysis of risks, opportunities, or scenarios. EMA aims to "cover the space" of possibilities, which can be described as the space being created by the uncertainty surrounding the many variables.

In EMA, relatively fast and simple computer models of the policy domain are applied. Because EMA aims to cover the whole space of possibilities, it is usually necessary to make huge numbers of computer runs (1,000–100,000 or more). With traditional best estimate models this would take too much time. With fast and simple models (low-resolution models), one can cover the entire uncertainty space, and then drill down into more detail where initial results suggest interesting system behavior (e.g., the boundaries between policy success and failure). Also, it is known that humans have a limited capability to process information (Simon 1978). Hence, to be able to base decisions on understandable logic implies not having too many variables or too much complexity. Thus, a relatively low-resolution model is preferable (Davis 2003).

The EMA practitioner is not interested in finding a single best policy given a validated predictive system model, but wants to display the pattern of policy performance over the entire uncertainty space of possible system models and external scenarios. Using a variety of visualization tools and analysis techniques, the results of the huge numbers of computer runs can be analyzed, displayed, and understood. Successfully applied algorithms in the context of EMA include the Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999) and Classification and Regression Trees (CART) (Breiman et al. 1984). Increasingly, such algorithms are available in standard statistical data analysis software packages (e.g., SPSS). The Evolving Logic company (evolvinglogic.com) produced a software environment called the Computer Assisted Reasoning system (CARs), which supports the generation of the EMA cases to be run and the manipulation and display of the results of the runs. And researchers at the Delft University of Technology are developing a 'workbench' aimed at providing support for performing EMA using models developed in a variety of modeling packages and environments.

One of the foundations of EMA is the idea that under conditions of Level 4 (and Level 5) uncertainty, analysts should explore multiple hypotheses about the system of interest by broadening the assumptions underlying a system model (Bankes 1993). Each of the hypotheses serves as one 'mirror', allowing policy analysts to look at the behavior of the system, and multiple mirrors provide a more reliable 'picture' than a single mirror does. Because each model run is treated as a deterministic hypothesis about the system of interest, EMA does not require assignment of likelihood or probability to uncertainty variables.

EMA explores the uncertainty regarding the effect of external factors by, for example, making separate runs using combinations of scenario variables. Different policy options and different strategies (combinations of policy options) can be simulated. The system structure can be explored by varying the relationships among the system's elements. For example, alternative functional relationships can be considered (thus addressing model uncertainty). This principle also applies to alternative parametric values, behavioral rules, or even theories. In the case of vague relationships (e.g., uncertainty about how two factors are correlated—whether one factor is the effect or the cause of other factors), analysts may also need to consider varying the magnitude and sign of the correlation coefficient, and, when causality is involved, varying the sign and/or direction of the cause–effect mechanism. Different combinations of assumptions form the hypotheses about the system underlying the decision problem.

In making policy decisions about complex and uncertain problems, EMA can provide new knowledge, even where validated models cannot be constructed. For example, multiple models that capture different framings of the same policy problem can be run. Instead of debating which is the right model, the policy debate can shift to the identification of policies that produce satisfying results across the different models.

EMA has also been used successfully for ‘scenario discovery’ (Lempert et al. 2006). The aim of scenario discovery is to analyze the results from a series of computational experiments in order to reveal which combinations of hypotheses and guesses were responsible for generating the results of interest. Results of interest can be identified based on the performance of candidate policies, but other criteria can also be used. One common use of scenario discovery is to identify combinations of external events that would lead to the failure of the policy being investigated. Scenario discovery has been used in the context of water resource management in California (Groves and Lempert 2007), for evaluating alternative policies considered by the United States Congress while debating reauthorization of the Terrorism Risk Insurance Act (Dixon et al. 2007), and for assessing the impact of a renewable energy requirement in the United States (Groves and Lempert 2007).

Agustinata (2008), Brooks et al. (1999), Kwakkel et al. (2012), and van der Pas et al. (2010) supply examples of how EMA can be applied to policy analysis problems involving Level 4 and Level 5 uncertainty. There is also ongoing work on expanding scenario discovery and EMA to consider the dynamics of a system and its behavior over time, which has been labeled Exploratory System Dynamics Modeling and Analysis (ESDMA) (Pruyt and Hamarat 2010a, b; Hamarat and Pruyt 2011a, b).

9.3.5 The Dynamic Adaptive Approach for Dealing with Level 5 Uncertainty

It is not the strongest of the species that survive, nor the most intelligent, but the ones most responsive to change.
– Charles Darwin

You can’t control the wind, but you can adjust your sails.
– Yiddish proverb

The concept of adaptive policies can be traced back to 1927, when John Dewey (1927) proposed that ‘policies be treated as experiments, with the aim of promoting continual learning and adaptation in response to experience over time’.

Early applications of adaptive policies, called Adaptive Management, can be found in the field of environmental management (Holling 1978). Motivated by the complexity of the environmental system, managers resort to controlled experiments aimed at increasing their understanding of the system (McLain and Lee 1996). Or, as Lee (1993) puts it, adaptive policies are 'designed from the outset to test clearly formulated hypotheses about the behavior of an ecosystem being changed by human use'.

A large literature review conducted at the International Institute for Sustainable Development found that the literature relating directly to the topic of adaptive policies is limited (IISD 2006). Walker et al. (2001) propose a structured, stepwise approach for adaptive policymaking, which is called Dynamic Adaptive Policymaking (DAP). DAP differs from adaptive approaches in the field of environmental management in that most of the key sources of uncertainty are external factors outside the control of the policymakers, instead of arising out of the complexity of the system the policymakers are trying to manage (although it can also take into account uncertainties in the structure of the system). Since the key sources of uncertainty are different, the approach also differs in several important respects from Adaptive Management. Most importantly, the approach advocates not only the development of a monitoring system but also the prespecification of responses when specific trigger values are reached. Adaptive policies combine actions that are time urgent with those that make important commitments to shape the future, preserve needed flexibility for the future, and protect the policy from failure.

The basic concept of a dynamic adaptive policy is easy to explain (Walker 2000b). It is analogous to the approach used in guiding a ship through a long ocean voyage. The goal—the end point—is set at the beginning of the journey. But, along the way, unpredictable storms and other traffic may interfere with the original trajectory. So, the policy—the specific route—is changed along the way. It is understood before the ship leaves port that some changes are likely to take place—and contingency plans may have already been formulated for some of the unpredictable events. The important thing is that the ultimate goal remains unchanged, and the policy actions implemented over time remain directed toward that goal (if the goal is changed, an entirely new plan must be developed). An adaptive policy would include a systematic method for monitoring the environment, gathering information, implementing pieces of the policy over time, and adjusting and readjusting to new circumstances. The policies themselves would be designed to be incremental, adaptive, and conditional.

Guiding the ship of state in this adaptive way may be revolutionary in many policy areas. However, new approaches to dealing with Level 4 uncertainties are gradually being accepted as valid—and, indeed, necessary. For example:

- In the financial area, as the example of Allan Greenspan indicates, financial planners have already seen that their standard models based on statistics and probabilities are insufficient to deal with the recent 'Black Swans'—such as the subprime mortgage and the debt ceiling debacles in the United States and the Greek debt crisis in Europe.

- Defense planners are beginning to understand that current defense planning methodologies need to be changed. For example, a recent draft report from a respected defense planning organization says "our current defence planning methodologies which still focus primarily on… trends and drivers that we presume to 'know'… insufficiently take into account the true nature of today's deep uncertainty."
- In the area of water management and flood safety, a report from the National Research Council of the US National Academy of Sciences notes that water management systems have traditionally been designed based on the assumption of stationarity (which means that the variability in their statistical patterns does not change over time, so that flood protection norms can be confidently based on past statistics). But, it concludes that "continuing to use the assumption of stationarity in designing water management systems is no longer practical or defensible" [National Research Council, Committee on Hydrologic Science (2011), p. 8].

The analysis and choice of an adaptive policy requires a new process for policymaking and policy implementation that explicitly takes into account the uncertainties and dynamics of the problem being addressed. DAP can be divided into two phases: a policy design phase, and a policy implementation phase. The policy design phase consists of five steps (see Fig. 9.8)—one step (Step I) that sets the stage for policymaking, three steps (Steps II, III, and IV) for designing the portions of the adaptive policy that get implemented initially (at time $t = 0$), and one step (Step V) that designs the portions of the adaptive policy that may be implemented in the future (at unspecified times $t > 0$). So, the implementation phase consists of two parts—implementation of the portions of the policy that get implemented initially (the portions that were designed in Steps II-IV) and adaptation of the initial policy (taking the actions that were designed in Step V).

9.3.5.1 The Design Phase: Steps in Designing a Dynamic Adaptive Policy

Figure 9.8 illustrates the DAP process. In particular, the following steps summarize the process for designing a dynamic adaptive policy.

Step I (stage setting) and Step II (assembling a basic policy)

The first and the second steps are basically the same as those that are carried out in designing a static policy using the traditional policy analysis process. The first step constitutes the *stage-setting* step. This step involves the specification of the system boundary and the objectives, constraints, and available policy options. This specification should lead to a definition of success, i.e., the specification of desirable outcomes.

In Step II, a *basic policy* is assembled. This step involves (a) the specification of a promising policy and (b) the identification of the conditions needed for the basic policy to succeed. These conditions will be used in Step III to set up a monitoring

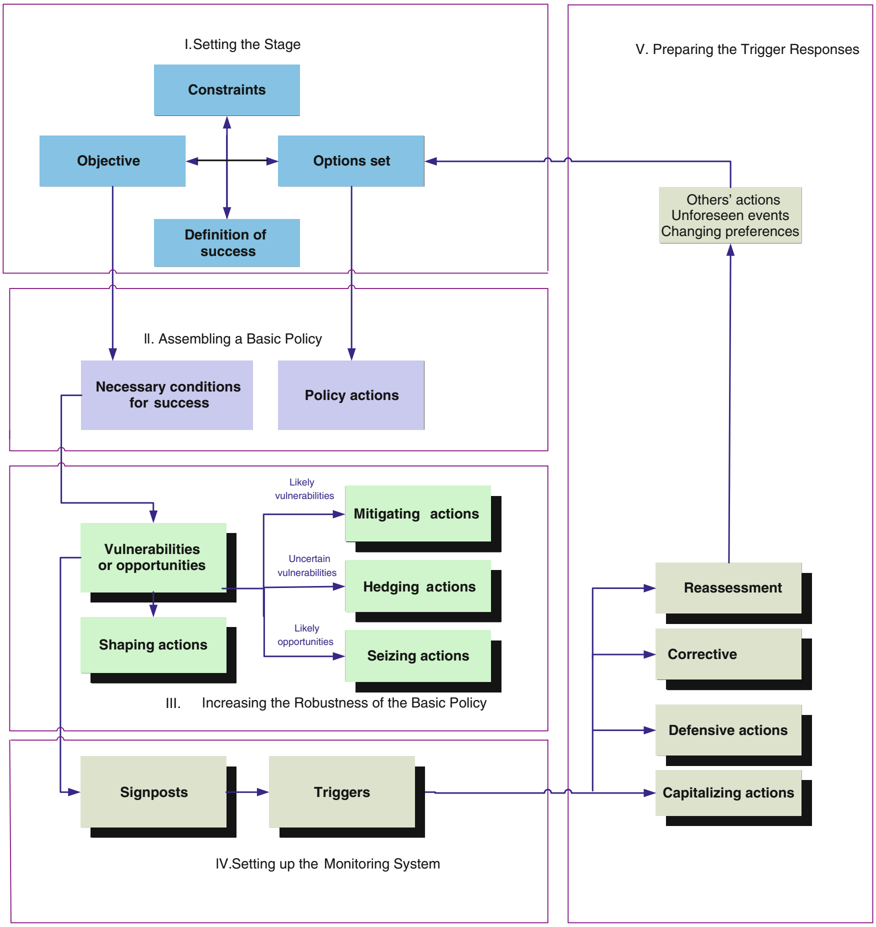


Fig. 9.8 The DAP process [*Source* Kwakkel et al. (2010a)]

system to provide advance warning in case conditions change and the policy might fail.

Step III (increasing the robustness of the basic policy)

In Step III of the DAP process, the actions to be taken immediately (i.e., at time t = 0) to enhance the chances of success of the policy are specified. This step is based on identifying in advance the vulnerabilities and opportunities associated with the basic policy, and specifying actions to be taken in anticipation (Step III) or in response (Steps IV and V) to them. *Vulnerabilities* are external developments that could degrade the performance of the policy so that it is no longer successful. *Opportunities* are external developments that could improve the performance of a policy so that it is more successful than it would have been without these external developments. Both likely and uncertain vulnerabilities and opportunities can be distinguished.

There are four different types of actions that can be taken in advance (at the time the basic policy is implemented—i.e., at time $t = 0$) in anticipation of specific contingencies or expected effects of the basic policy:

- *Mitigating actions* (*M*)—actions to reduce the *likely* adverse effects of the basic policy;
- *Hedging actions* (*H*)—actions to spread or reduce the risk of *uncertain* adverse effects of the basic policy;
- *Seizing actions* (*SZ*)—actions taken to seize *likely* available opportunities;
- *Shaping actions* (*SH*)—actions taken to reduce the chance that an external condition or event that could make the policy fail will occur, or to increase the chance that an external condition or event that could make the policy succeed will occur.

Mitigating actions and hedging actions prepare the basic policy for potential adverse effects and in this way try to make this policy more robust. Seizing actions are actions taken at $t = 0$ to change the policy in order to seize available opportunities. In contrast, shaping actions are proactive and aim at affecting external factors in order to reduce the chances of negative outcomes or to increase the chances of positive outcomes. As such, shaping actions aim not so much at making the plan more robust, but at changing the external situation in order to change the nature of the vulnerability or opportunity.

Scenarios are very useful for identifying vulnerabilities and opportunities, and for identifying mitigating, hedging, and seizing actions for handling them. We use van der Heijden's (1996, p. 5) definition of an "external scenario". He says "external scenarios… are created as internally consistent and challenging descriptions of possible futures… What happens in them is essentially outside our own control." The scenarios are used to identify the ways in which the basic policy could go wrong (i.e., not lead to success) or to identify emerging opportunities that should be seized. The primary focus should be on the "plot"—the story that connects the present with how the basic policy might fail, and what that failure would lead to.

The primary challenge in using scenarios in DAP is to make them credible. Often, the most credible scenario of the future will be the one that is most like the present. However, in DAP, since we are looking for changes in the world that can make the basic policy fail or produce unanticipated success, the scenarios should

[4] Thomas Schelling, in a Foreward to Wohlstetter's (1962) study *Pearl Harbor: Warning and Decision,* wrote "There is a tendency in our planning to confuse the unfamiliar with the improbable. The contingency we have not considered seriously looks strange; what looks strange is thought improbable; what is improbable need not be considered seriously".

differ from the present in major ways. Very negative scenarios are likely to lack credibility; research (see Janis and Mann 1977) suggests that people tend to view very negative scenarios as implausible and reject them out of hand. Nevertheless, they are crucial to an adaptive policy; having thought about a situation (no matter how implausible) in advance allows contingency plans to be formulated so that they are ready to be implemented in the (however unlikely) event they are needed.[4]

EMA is also a useful approach in this step and in Steps IV and V (see Chap. 7). EMA can be used for exploring the consequences of violating the assumptions underlying the basic policy. A single run of an assumed model structure and parameterization of that structure constitutes a computational experiment that reveals how the real world would behave if the various guesses were correct. By conducting a series of such computational experiments, one can explore the implications of the various assumptions and hypotheses. For situations that turn out very bad (or very good), actions can be taken to guard against them (or take advantage of them).

Step IV (setting up the monitoring system) and Step V (preparing the trigger responses)

Even with the actions taken in advance, there is still a need to monitor changes in the world and the performance of the policy and to take actions if needed to guarantee the policy's progress and success. In this step, *signposts* are identified that specify information that should be tracked, and critical values of signpost variables (*triggers*) are specified beyond which actions to change the policy should be implemented to ensure that the resulting policy keeps moving the system in the right direction and at a proper speed. The starting point for the identification of signposts is the set of vulnerabilities and opportunities specified in Step III.

There are four different types of actions that can be triggered by a signpost:

- *Defensive actions* (*DA*)—actions taken *after the fact* to clarify the policy, preserve its benefits, or meet outside challenges in response to specific triggers that leave the basic policy unchanged;
- *Corrective actions* (*CR*)—adjustments to the basic policy in response to specific triggers;
- *Capitalizing actions* (*CP*)—actions taken *after the fact* to take advantage of opportunities that further improve the performance of the basic policy;
- *Reassessment* (*RE*)—a process to be initiated or restarted when the analysis and assumptions critical to the policy's success have clearly lost validity.

9.3.5.2 The Implementation Phase

Once the basic policy and additional actions are agreed upon, the entire adaptive policy is implemented. In this phase, the actions to be taken immediately (from Step II and Step III) are implemented and a monitoring system (from Step IV) is established. Then time starts running, signpost information related to the triggers is collected, and policy actions (from Step V) are implemented.

After implementation of the initial mitigating, hedging, seizing, and shaping actions, the implementation process is suspended until a trigger event occurs. As long as the original policy objectives and constraints remain in place, the responses to a trigger event have a defensive or corrective character—that is, they are adjustments to the basic policy that preserve its benefits or meet outside challenges. Sometimes, opportunities are identified by the monitoring system, triggering the implementation of capitalizing actions. Under some circumstances, neither defensive nor corrective actions might be sufficient to save the policy. In that case, the entire policy might have to be reassessed and substantially changed or even abandoned. If so, however, the next policy deliberations would benefit from the previous experiences. The knowledge gathered in the initial policy-making process on outcomes, objectives, measures, preferences of stakeholders, etc., would be available and would accelerate the new policymaking process.

9.4 An Illustrative Example of DAP: Airport Strategic Planning[5]

Airport Strategic Planning (ASP) focuses on the development of plans for the medium- and long-term development of an airport. The dominant approach for ASP is Airport Master Planning (AMP). The goal of AMP is to provide a detailed blueprint for how the airport should look in the future, and how it can get there (Burghouwt and Huys 2003). In general, airports do not have a good track record for making good long-term decisions (Kwakkel et al. 2010a). Since a Master Plan is a static detailed blueprint based on specific assumptions about the future, the plan performs poorly if the real future turns out to be different from the one assumed. AMP results in poorly performing plans, primarily because it fails to take uncertainties about the future into account in a proper way. With the recent dramatic changes occurring in the context in which an airport operates (e.g., low-cost carriers, new types of aircraft, the liberalization and privatization of airlines and airports, fuel price developments, the European Emission Trading Scheme), the uncertainties airports face are increasing. Hence, there is an even greater need for finding new ways to deal with uncertainty in ASP. Static Master Plans are poorly equipped to deal with the many uncertainties. An alternative direction is to use DAP to develop an adaptive policy that is flexible and over time can adapt to the changing conditions under which an airport must operate.

Phase 1: Policy Design

Step I: Specification of objectives, constraints, and available policy options

[5] This section is based upon Kwakkel et al. (2010a).

The Schiphol Group is primarily interested in medium- to long-term developments through the year 2020. As outlined in its current long-term vision (Schiphol Group 2007), the main goals of the Schiphol Group are: (1) to create room for the further development of the network of KLM and its Skyteam partners, and (2) to minimize (and, where possible, reduce) the negative effects of aviation in the region. Underlying the first goal is the implicit assumption that aviation will continue to grow. However, in light of recent developments such as peak oil and the financial crisis, this assumption is questionable. It might be better to rephrase this first goal more neutrally as 'retain market share'. If aviation in Europe grows, Schiphol will have to accommodate more demand in order to retain its market share, while if aviation declines, Schiphol could still reach its goal of retaining market share.

There are several types of changes that can be made at Schiphol in order to achieve its goals of retaining market share and minimizing the negative effects of aviation. Schiphol can expand its capacity by using its existing capacity more efficiently and/or building new capacity. It can also expand its capacity or use its existing capacity in a way that mitigates the negative effects of aviation. More explicitly, among the policy options that Schiphol might consider are:

1. Add a new runway
2. Add a new terminal
3. Use the existing runway system in a more efficient way, in order to improve capacity
4. Use the existing runway system in a way that minimizes noise impacts
5. Move charter operations out of Schiphol (e.g., to Lelystad)
6. Move Schiphol operations to a new airport (e.g., in the North Sea)
7. Invest in noise insulation

Some of these policies can be implemented immediately (e.g., using the existing runway system in a more efficient way). For others, an adaptive approach would be to begin to prepare plans and designs (e.g., for a new runway), but to begin actual building only when conditions show it to be necessary (i.e., when it is triggered). The various options can, of course, be combined. The changes that can be made are constrained by the budget, spatial restrictions, public acceptance, and the landside accessibility of Schiphol. The definition of success includes that Schiphol maintains its market share and that living conditions improve compared to some reference situation (e.g., number of people affected by noise within a specified area).

Step II: A basic policy and its conditions for success

A basic policy might be to immediately implement existing plans for using the runways more efficiently (option 3) and in a way that reduces noise impacts (option 4). It might also include all policy options that focus on planning capacity expansions, without beginning to build any of them (i.e., options 1, 2, and 5). A final element of the basic policy might be option 7: invest in noise insulation. The choice for only planning capacity expansions but not yet building them is motivated by the fact that Schiphol is currently constrained by the environmental rules and regulations, not by its physical capacity. This also motivates the choice for options 3 and 4, which together can reduce the negative externalities of aviation.

In light of Schiphol's twin goals of retaining market share and minimizing the negative effects of aviation (Schiphol Group 2007), several necessary conditions for the success of the basic policy can be specified:

- Schiphol should retain its current market share
- The population affected by noise and the number of noise complaints should not increase
- Schiphol's competitive position in terms of available capacity in Europe should not decrease
- Schiphol's landside accessibility should not deteriorate

Step III: Vulnerabilities and opportunities of the basic policy, and anticipatory actions

The long-term development of Schiphol is complicated by the many and diverse trends and developments that can affect Schiphol. These developments and trends present both opportunities and vulnerabilities. Some of these vulnerabilities are relatively certain. These are given in Table 9.1. Two likely vulnerabilities are resistance from stakeholders and a reduction of the landside accessibility. The mitigating actions for addressing these vulnerabilities are very similar to actions currently being discussed by the Dutch Government. A shaping action for the vulnerability of landside accessibility is investment in research. In addition to vulnerabilities, there are currently also some opportunities available to Schiphol. First, recent work shows the potential for 'self-hubbing' (Burghouwt 2007; Malighetti et al. 2008). Self-hubbing means that passengers arrange their own flights and routes, using low-cost carriers or a variety of alliances, in order to minimize costs and/or travel time. Schiphol has a great potential for attracting such self-hubbing passengers, because it connects 411 European cities (Malighetti et al. 2008). Schiphol can seize this opportunity by developing and implementing services tailored to self-hubbing passengers, such as services for baggage transfer and help with acquiring boarding passes. Furthermore, Schiphol could take into account walking distances between connecting European flights when allocating aircraft to gates. A second opportunity is presented by the fact that airports in general, and Schiphol in particular, are evolving into 'airport cities'. Given the good transport connections available, an airport is a prime location for office buildings. Schiphol can seize this opportunity by investing in non-aeronautical landside real estate development.

Not all vulnerabilities and opportunities are likely. The real challenge for the long-term development of Schiphol is presented by the *uncertain* vulnerabilities and opportunities. Table 9.2 presents some of the uncertain vulnerabilities together with possible hedging (H) and shaping actions (SH) to be taken right away to handle them. The vulnerabilities and opportunities can be directly related and

Table 9.1 Likely vulnerabilities and opportunities, and responses to them

Vulnerabilities and opportunities	Mitigating (M), Shaping (SH), and Seizing (SZ) actions
Reduction of the landside accessibility of the airport	**M**: develop a system for early check-in and handling of baggage at rail stations **SH**: invest in R&D into the landside accessibility of the Randstad area
Resistance from Schiphol stakeholders (e.g., environmental groups, people living around Schiphol)	**M**: develop plans for green areas to compensate for environmental losses **M**: offer financial compensation to residents in the high noise zone
Rise of self-hubbing	**SZ**: design and implement a plan for supporting self-hubbing passengers with finding connection flights, transferring baggage, and acquiring boarding passes
Rise of the airport city	**SZ**: Diversify revenues by developing non-aeronautical landside real estate

categorized according to the success conditions specified in the previous step. With respect to the success condition of growing demand, air transport demand might develop significantly differently from what is hoped and anticipated. Schiphol can respond to this by making Lelystad airport suitable for handling non-hub-essential flights. Another vulnerability is that KLM might decide to move a significant part of its operations to Charles de Gaulle. This will leave Schiphol without its hub carrier, significantly reducing demand, and changing the demand to origin–destination demand. Schiphol could prepare for this vulnerability by making plans for adapting the terminal to the requirements of an O/D airport and by diversifying the carriers that serve Schiphol. Schiphol can also try to directly affect KLM by investing in a good working relationship, reducing the chance that KLM will leave. Currently, there is an ongoing debate about the future of the hub-and-spoke network structure. Due to the Open Sky agreements and the development of the Boeing 787, long-haul low-cost, hub bypassing, and self-hubbing become plausible, resulting in the emergence of long-haul low-cost carriers (LCCs) and increasing transfer between short-haul low-cost, and long-haul carriers (both LCC and legacy carriers). Schiphol can prepare for this by developing a plan to change its current terminal to serve a different type of demand and by taking these plausible developments into consideration when designing the new LCC terminal and its connection with the existing terminal. If a transformation to international origin–destination traffic and/or a no-frills airport is needed, this plan can be implemented, making sure that the transformation can be achieved quickly.

The second success condition is that the population affected by noise and the number of noise complaints should not increase. Vulnerabilities and opportunities associated with this condition are that the current trend of decreases in the

Table 9.2 Uncertain vulnerabilities and opportunities, and responses to them

Vulnerabilities and opportunities	Hedging(H) and Shaping(SH) actions
Retain market share	
Demand for air traffic grows faster than forecast.	**H**: Prepare Lelystad airport to receive charter flights
Demand for air traffic grows slower than forecast.	**SH**: Advertise for flying from Schiphol
Collapse or departure of the hub carrier (KLM) from Schiphol.	**H**: Prepare to adapt Schiphol to be an O/D airport. **H**: Diversify the carriers serving Schiphol **SH**: Develop a close working relation with KLM
Rise of long-haul low-cost carriers	**H**: Design existing and new LCC terminal to allow for rapid customization to airline wishes
Rise of self-hubbing, resulting in increasing transfers among LCC operations	**H**: Design a good connection between the existing terminal and the new LCC terminal, first with buses, but leave room for replacing it with a people mover
Population affected by noise and the number of noise complaints should not increase	
Maintain current trend of decrease of environmental impact of aircraft	**SH**: *N*egotiate with air traffic control on investments in new air traffic control equipment that can enable noise abatement procedures, such as the continuous descent approach **SH**: Invest in R&D, such as noise abatement procedures
Increase in the population density in area affected by noise	**H**: Test existing noise abatement procedures, such as the continuous descent approach, outside the peak periods (e.g., at the edges of the night) **SH**: Negotiate with surrounding communities to change their land use planning **SH**: Invest in R&D, such as noise abatement procedures
Change in the valuation of externalities by the public	**SH**: Invest in marketing of the airport to brand it as an environmentally friendly organization **SH**: Join efforts to establish an emission trading scheme
Schiphol's competitive position in terms of available capacity in Europe does not decrease	
Other major airports in Europe increase capacity	No immediate action required
Development of wind conditions due to climate change	**H**: Have plans ready to quickly build the sixth runway, but do not build it yet. If wind conditions deteriorate even further, start construction

environmental impact of aircraft changes, the population density in the area affected by noise increases, and the valuation of externalities (predominantly noise) by the large public changes. If the current trend of decreasing environmental impact slows down, the area affected by noise will not continue to shrink if demand stays the same. If demand increases, it is possible that the area affected by noise will also increase.

On the other hand, the trend could also accelerate, giving Schiphol the opportunity to expand the number of flights that is handled. Given the potential impact of this trend, Schiphol should try and shape its development by investing in R&D and negotiate with Air Traffic Control about testing noise abatement procedures, such as continuous descent approaches. If the population density changes, the situation is similar. If it increases, the number of people affected by noise will increase, while if it decreases, the number of people affected by noise will decrease. Schiphol can try and shape this development by negotiating with surrounding communities about their land use planning and invest in research that can make the area affected by noise smaller. It can also hedge against a growing population density by starting to test noise abatement procedures outside peak hours. This will make the area affected by noise smaller. Thus, even if the population density increases, the total number of people affected will not increase. A third uncertainty is how the valuation of noise will change in the future. If noise will begin to be considered more of a nuisance, complaints are likely to go up, and vice versa. Schiphol could try to affect this valuation by branding the airport as environmentally friendly and supporting the development of an emission trading scheme that also includes aviation.

The third success condition is that Schiphol's competitive position in terms of available capacity in Europe does not decrease. Schiphol is vulnerable to the capacity developments at other airports in Europe. The major hubs in Europe are all working on expanding their capacities, either by adding runways and expanding terminals, or by moving non-hub-essential flights to alternative airports in the region. Schiphol should monitor these developments closely and, if necessary, speed up its capacity investments. A second vulnerability is the robustness of Schiphol's peak-hour capacity across weather conditions. Under southwesterly wind conditions, Schiphol's hourly capacity is almost halved, resulting in delays and cancellations. If (e.g., due to climate change) these wind conditions were to become more frequent, Schiphol would no longer be able to guarantee its capacity. Schiphol should hedge against this by having plans ready for building a sixth runway.

Step IV and Step V: Adding adaptivity

Step IV sets up the monitoring system and identifies the actions to be taken when trigger levels of the signposts are reached. The vulnerabilities and opportunities are those presented in Table 9.2. Table 9.3 shows the signpost to be set up for each vulnerability and each opportunity, and the possible responsive actions in case of a trigger event. The numbers used as triggers are for illustrative purposes only. For example, if demand increases twice as fast as expected, this presents an opportunity and would trigger a capitalizing action. If demand grows 25 % slower than anticipated, this presents a threat to the policy. In reaction, investments in capacity should be delayed or even canceled. If demand fully breaks down or explodes, the policy should be reassessed.

Phase 2: Policy Implementation

In the implementation phase, the adaptive policy is implemented. This policy consists of the basic policy specified in Step II, the actions specified in Tables 9.1

Table 9.3 Adding adaptivity

Vulnerabilities and opportunities	Monitoring and trigger system	Actions [Reassessment (RE), Corrective (CR), Defensive (DA), Capitalizing (CP)]
Retain market share		
Demand for air traffic grows faster than forecast	Monitor the growth of Schiphol in terms of passenger movements, aircraft movements (and related noise and emissions), if double demand (trigger) take CP-action. If demand explodes, take RE-action	**CP**: Begin to implement the plan for the new terminal and the new runway **RE**: Reassess entire policy
Demand for air traffic grows slower than forecast	Monitor types of demand. If overall demand is decreasing by half of forecast, take D-actions. If demand fully breaks down, take RE-action. If transfer rate decreases below 30 % take CR-action	**DA**: Delay investments, and reduce landing fees **RE**: Reassess entire policy **CR**: Cancel terminal capacity expansions
Collapse or departure of the hub carrier (KLM) from Schiphol	Monitor the network of KLM-Air France, if 25 % of flights are moved take DA-action, if 50 % take CR-action, if 80 % or more take R-action	**DA**: Diversify the carriers that fly from Schiphol **CR**: Switch airport to an O/D airport by changing terminal **RE**: Reassess entire policy
Rise of long-haul low-cost carriers	Monitor development of the business model of low-cost carriers. If long-haul LCC carriers make profit for 2 years take CP-action	**CP**: Attract long-haul LCC by offering good transfer between LCC terminal and existing terminal and/or by offering wide body aircraft stands at the LCC terminal
Rise of self-hubbing, resulting in increasing transfers between LCC operations	Monitor transfer rate among LCC flights and between LCC and legacy carriers. If transfer rate becomes more then 20 %, take CP-action	**CP**: Expand transfer capabilities between the new LCC terminal and the existing terminal
Population affected by noise and the number of noise complaints should not increase		
Maintain current trend of decrease of environmental impact of aircraft	Monitor noise footprint and emissions of the fleet mix serving Schiphol and of the new aircraft entering service. If there is an increase of noise or emissions of 10 %, take CR-action	**CR**: Change landing fees for environmentally unfriendly planes
Increase in the population density in area affected by noise	Monitor population affected by noise. If population affected by noise increases by 2 %, take DA-action; by 5 %, take CR-action; by 7.5 %, take R-action. If population density decreases by 2 %, take CP-action	**DA**: Expand insulation program and explain basic policy again **CR**: Slow down of growth by limiting available slots **RE**: Reassess entire policy **CP**: If the population density decreases, make new slots available

(continued)

Table 9.3 (continued)

Vulnerabilities and opportunities	Monitoring and trigger system	Actions [Reassessment (RE), Corrective (CR), Defensive (DA), Capitalizing (CP)]
Change in the valuation of externalities by the large public	Monitor the complaints about Schiphol. If complaints increase by an average of 5 % over two years, take DA-action. If complaints increase by an average of 10 % or more over two years, take CR-action	**DA**: Increase investments in marketing and branding **CR**: Slow down the growth of Schiphol by limiting the available slots
Schiphol's competitive position in terms of available capacity in Europe does not decrease		
Other major airports in Europe increase capacity	Monitor declared capacity for the major airports in Europe. If declared capacity is up by 25 %, take D-action	**DA**: Speed up expansions
Development of wind conditions due to climate change	Monitor the prevailing wind conditions throughout the year. If for two years in a row the number of days with cross-wind conditions exceeds 50, take D-action	**DA**: Begin to implement the plan for the new runway

and 9.2, and the monitoring system specified in Table 9.3. Note that the new runway being planned in the basic policy is not built yet, but can be built when necessary in light of demand increases or capacity increases at other major European airports. As such, it is a 'real option'. The same is true of the new terminal. All the preparatory work should be started, including the clearing of the land, relocation of the current facilities on the location to other places, and putting in place the required utilities (e.g., electricity, sewers, water, space for a connection to the existing terminal, connections to the highway system and the rail system). Construction should begin if triggered by demand developments or capacity developments at other airports.

During the implementation phase, Schiphol would monitor developments. Suppose the signposts indicate that Schiphol is maintaining its position as a major airport for the Skyteam alliance and its partners and its demand is growing faster than anticipated in the plan, but that the boundaries set for safety, the environment, and quality of life, and spatial integration with its surroundings are being violated. Construction of the new terminal can start. In addition, actions need to be taken to defend the policy with respect to the negative external effects. The noise insulation program can be expanded and more investment can be made in branding and marketing that aim at explaining the policy. If these actions prove to be insufficient, the noise insulation program can be expanded, Schiphol should start to buy out residents that are heavily affected by noise, and increase landing fees for environmentally unfriendly planes. If this still is insufficient, Schiphol should consider limiting the number of available slots, especially during the night and edges of the night. If these actions are still insufficient, either because demand grows very fast or because the environmental impact grows too fast, the policy should be reassessed. In the case of reassessment, the decisionmakers would repeat the DAP steps in order to develop a new (adaptive) policy.

9.5 Conclusions

The world is undergoing rapid changes. The future is uncertain. Even with respect to understanding existing natural, economic, and social systems, many uncertainties have to be dealt with. Furthermore, because of the globalization of issues and the interrelationships among systems, the consequences of making wrong policy decisions have become more serious and global—potentially even catastrophic. Nevertheless, in spite of the profound and partially irreducible uncertainties and serious potential consequences, policy decisions have to be made. Policy analysis aims to provide assistance to policymakers in developing and choosing a course of action, given all of the uncertainties surrounding the choice.

That uncertainties exist in practically all policymaking situations is generally understood by most policymakers, as well as by most policy analysts. But there is little appreciation for the fact that there are many different dimensions of uncertainty, and there is a lack of understanding about their different characteristics, their relative magnitudes, and the available approaches and tools for dealing with them.

This chapter has shown that policy analysts already have many analytic tools and approaches for dealing with uncertain situations. They are still appropriate in many cases. However, before any one of them is used, it is important to identify the location, level, and nature of the uncertainties related to the particular case, and their relative importance, and only then to choose an appropriate approach.

There are many approaches that have been shown to be appropriate for handling Level 1 and Level 2 uncertainties. However, it is not appropriate to treat Level 3, Level 4, and Level 5 uncertainties with these same approaches. For example, an implicit assumption using Level 1 approaches is that the future world will be structurally more or less the same as the current world—perhaps more populated, richer, dirtier—but, essentially the same. If, in reality, the uncertainties are deeper, such an approach can have serious consequences. For example, as discussed by de Neufville (2000), the telephone company of France was a pioneer in the use of on-line interactive telecommunications. It committed itself, on the basis of the most careful analyses, to the development of the Minitel system. But, it failed to build in the capability to change as the world changed—to expand to more advanced platforms using improved technologies for the system. This resulted in a network that is obsolete in the Internet environment, and that cannot practically be adapted to the new technical realities. It became a dinosaur less than 30 years after its initiation and was completely abandoned in 2012.

The scenario approach may be appropriate for Level 3 and Level 4 uncertainties. The central assumption of this paradigm is that the future can be predicted well enough to identify policies that will produce favorable outcomes in one or more specific plausible future worlds. If this range of future worlds covers the full spectrum well, then the resulting policy has a fair chance of being successful. However, if some of the underlying assumptions about the future turn out to be wrong, the negative consequences can be as bad as if uncertainty about the future had been totally ignored.

Level 1, 2, 3, and 4 approaches are not appropriate in the face of Level 5 uncertainty. New approaches are needed. One possible approach is dynamic adaptation, which offers a clear structure and tools for thinking about and evaluating uncertainties and making explicit tradeoffs. While we may not be able to foresee all of the consequences of an uncertain future, dynamic adaptation offers a way to protect ourselves from nasty surprises and unforeseen contingencies, and to begin to implement a policy to address the problem right away.

DAP helps us make more robust plans by accepting uncertainty and acknowledging that we cannot know the future (even probabilistically). The approach calls for implementing a basic policy based on what we know today, and constructing a system for monitoring the (unpredictable) developments that could potentially affect the effectiveness of the chosen policy. The resulting policy is dynamic; the element of time and the possibility of learning are explicitly taken into account by the policy. Whereas, other approaches are based on the notion that policymaking is a discrete one-time event and that the resulting policy is static, dynamic adaptation is explicitly defined as a continuous process in time that involves monitoring and making prespecified changes to existing policy in response to unforeseen developments.

Dynamic adaptation has not yet been implemented in practice. However, in addition to the airport strategic planning case presented in Sect. 9.4, various other areas of application of DAP have been explored, including flood risk management in the Netherlands in light of climate change (Rahman et al. 2008), seaport planning (Taneja et al. 2011) 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). In 2012, a pilot test of the DAP approach was made with respect to the management of the Rhine Delta region of the Netherlands in the face of deep uncertainty about global warming and sea level rise.

But, more research is required before DAP is ready for full implementation. First, its validity and efficacy needs to be established. This will be difficult to do since, as Dewar et al. (1993) have pointed out, ''nothing done in the short term can 'prove' the efficacy of a planning methodology; nor can the monitoring, over time, of a single instance of a plan generated by that methodology, unless there is a competing parallel plan.'' Nevertheless, evidence is being gathered through a variety of methods, including gaming and computational experiments using EMA. (Using Exploratory Modeling and Analysis, Kwakkel et al. (2012) demonstrate the efficacy of DAP for the airport strategic planning case in Sect. 9.4). Also, the costs and benefits of dynamic adaptation measures compared to traditional policymaking approaches need to be studied. (Using real options analysis, Yzer (2011) shows that, for the airport strategic planning case in Sect. 9.4, DAP is likely to be more cost-beneficial than traditional Master Planning). Finally, the implementation of dynamic adaptation will require significant institutional/governance changes, since some aspects of these policies are currently not supported by laws and regulations (e.g. the implementation of a policy triggered by an external event). Lempert and Light (2009) provide some suggestions about a governmental framework at the national level in the United States that could support the implementation of this type policymaking.

Nevertheless, the DAP framework offers several advantages over other approaches. Most important of these are (1) it does not ignore uncertainty; it acknowledges that we cannot know the future and bases policy on this assumption, and (2) it institutionalizes the process of ex-post policy evaluation and monitoring. As Nassim Nicholas Taleb (2007) has written: ''It is often said that 'is wise he who can see things coming.' Perhaps, the wise one is the one who knows that he cannot see things far away.''

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