2

Decision Making Under Uncertainty

2.1. INTRODUCTION

Making good decisions is important in many aspects of life. Decisions in the personal realm are made by individuals and usually consider the consequences of those decisions on others (e.g., family members). In organizations (e.g., corporations, governments, universities, etc.), individuals also play a critical role in decision making, but they are usually part of a group-based decision-making process. How does an individual or an organization know whether they are making a good decision at the time they are making that decision (without the benefit of hindsight)? Would you know a good decision if you saw one? Without any field-specific knowledge one could be inclined to define decision making as "choosing between many alternatives that best fits your goals." However, the evident questions then are (i) how to define what is best or optimal, requiring the definition of some criterion, which may change the decision if this criterion changes and (ii) what are the stated goals? Decision analysis theory provides axiomatic scientific tools for addressing these questions in a structured, repeatable way.

Uncertainty plays a very important role in making sound decisions. The existence of uncertainty does not preclude one from making a decision. Decisions can be made without perfect information. A poor way of proceeding is to make a decision first and then question whether particular events were uncertain. Decision making and uncertainty modeling is an integral and synergetic process, not a sequential set of steps.

In most meaningful circumstances, a decision can be defined as a conscious, irrevocable allocation of resources to achieve desired objectives [*Howard*, 1966]. This definition very much applies to any type of geo-engineering situation. The decision to drill a well, cleanup a site, construct aquifer storage and recovery facilities, or re-allocating water abstraction requires a clear commitment of resources. One may go even to a higher level and consider policy making by government or organizations as designed to affect decisions to achieve a certain objective.

Ron Howard who was at the forefront of decision making as a science describes this field as a "systematic procedure for transforming opaque decision problems into transparent decision problems by a sequence of transparent steps." Applying the field of decision analysis to subsurface systems is not trivial because it involves the following:

1. *Uncertainty*. While most of this book addresses the geoscience aspect of uncertainty as it pertains to the measurements and models we establish to make prediction and optimize profit or use of resources, there may be many other sources of uncertainty, more related to the economic portion of uncertainty (costs, prices, human resources) or human behavior that are not discussed in this book.
2. *Complexity*. Rarely does one make a single decision on a single decision question. Often a complex sequence of decisions needs to be made. This is certainly the case in oil field production where engineers need to make decisions on facility or well location and well-types as the field is being produced.
3. *Multiple objectives*. Often, competing objectives exist in decision making, for example as related to safety and environmental concern compared to the need for energy resources.
4. *Time component*. If it takes too much time to quantify uncertainty that tries to include all sorts of complexity, and the decision must be made in a much shorter time frame, then a complex model ends up having little input into the decision. This is often the case in a time-sensitive business or industries (competitive oil-field reserve calculations, for example). In such cases, one may want to employ simpler models of uncertainty over complex ones.

This chapter provides a basic overview of those elements of decision analysis that are important in the

Quantifying Uncertainty in Subsurface Systems, *Geophysical Monograph 236*,
First Edition. Céline Scheidt, Lewis Li, and Jef Caers.

context of the subsurface. The purpose is not to be exhaustive by any means, instead to be more illustrative of concepts that may be new to some readers. The following publications are recommended as introductory material:

Foundation of Decision Analysis [*Howard and Abbas*, 2015]. This book is based on course notes that Ronald Howard used for teaching decision analysis at Stanford. This is one of the gold standard texts in decision analysis.

Handbook of Decision Analysis [*Parnell et al.*, 2013]. As an excellent introduction to the topic, it covers next to the more axiomatic component of decision analysis, the soft skills that are needed to make good decisions.

Value of Information in the Earth Sciences [*Eidsvik et al.*, 2015]. This publication looks at decision analysis with a spatial context as well as values information analysis with many applications in the Earth sciences.

Making Good Decisions [*Bratvold and Begg*, 2010]. This book focuses on the petroleum industry, but it is an excellent easy read for those looking to be exposed to the subject matter.

2.2. INTRODUCTORY EXAMPLE: THE THUMBTACK GAME

To illustrate some basic concepts in decision making, let us play a game. Imagine you are offered an opportunity to win \$100. The game is simple. A thumbtack will be tossed with two possible outcomes, "pin up" and "pin down"; if you guess correctly, you win \$100, otherwise you get nothing. However, there is no free lunch; you need to go into competition with other players to buy your way into this opportunity to bet. In other words, the opportunity will be auctioned off. This auction can be done under varying rules: closed first price, closed second price (Vickrey auction, e.g., E-bay), open descending (Dutch auction), or open ascending (English auction).

Regardless of the auction, someone will get the opportunity and pay an amount for it. Imagine you won the auction by offering \$20. This \$20 is now gone, you will never see it again. In decision analysis, this is termed a "sunk cost." In rational decision making, sunk costs should be ignored; in other words, one should not have a sentimental attachment such as "I already invested so much in the project; that means I need to keep investing, because I feel committed to it." Future decisions will not and should not be affected by sunk costs; they will only affect net-profit. Sunk costs are about the past, decisions are about the future. Figure 2.1 describes this situation with a decision tree (a logical time-dependent arrangement of decisions, uncertainties, and payoffs, see Section 2.5).

The decision tree allows introducing a few more concepts:

1. *A scenario*. An instantiation of every decision situation, here it is the combination of your call with the outcome (four possibilities).

2. *A prospect*. How the decision maker views the future for each scenario. It is the equivalent of "outcome" in probability theory.

3. *A lottery (gambles or deals)*. A situation with uncertain prospects without a decision being made. For example, you could be told to call pin down, without having a say in this. Then you face a lottery.

After paying \$20, you get a certificate that gives you the right to bet on the game. Let us now consider the following question: What is the least amount of dollars you are willing to sell this certificate for? There is no objective answer, it depends on your willingness to sell it at a high or low price, and hence we need to introduce a second

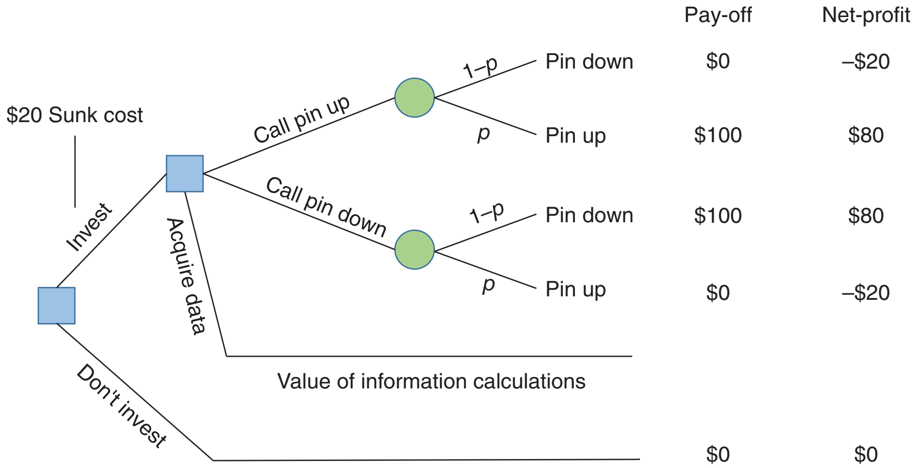

Figure 2.1 Decision tree for a simple game of investing and betting. Squares represent decisions nodes and circles represent uncertainty nodes.

important component: utility. All situations that face decisions and uncertainty require only two basics concepts: probability and utility. A utility represents the decision maker's preference for lotteries with uncertain value prospects. A risk neutral decision maker takes values as they are and takes the alternative that maximizes expected value. To account for risk averse or risk-seeking decision makers, a utility function is introduced to map the value into a new value termed "utility" [*Von Neumann and Morgenstern*, 1944], which is between 0 and 1 or 0 and 100 (see Figure 2.2).

Let us now return to the question of selling your certificate. We now introduce the concept of certainty equivalent (CE) which is the certain amount in your mind that you are willing to sell the certificate for. In more formal language, it is the amount where the decision maker is indifferent between selling it and retaining it. Logically then, the difference between the expected prospect and the CE reflects your attitude toward risk.

$$\text{Risk premium} = \text{expected value} - \text{certainty equivalent}$$

The expected value in this binary game is simply

$$E[\text{payoff}] = P(\text{correct call}) \times \$100$$

which is not known in this case because we do not know the probabilities related to tossing a thumbtack. In a Bayesian sense, we could assume some prior distribution on this (see Chapter 5 and the billiard table example). Therefore, this probability reflects our state of knowledge, it is not a property of the thumbtack. Indeed, if we know the outcome of the toss, then this probability is simply one. Risk neutral investors will have a CE equal to the expected value (they sell the certificate for a price equal to what they consider the expected payoff). Risk averse investors will be conservative and sell it for a low price to make sure they get paid at least some amount for certain (note that the sunk cost does not come into play here). Risk-seeking investors are willing to set high prices, with the risk of getting paid nothing by entering risky investments. For the same utility, risk seekers have higher CE (see Figure 2.2).

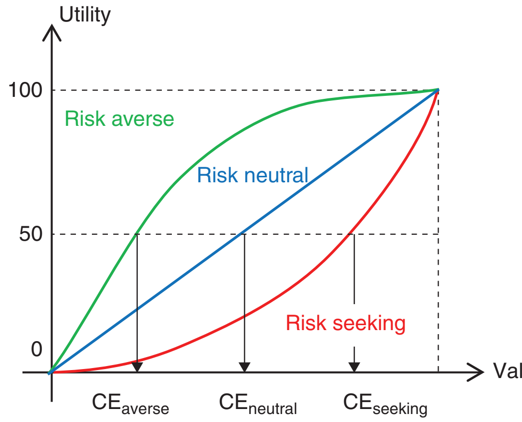

Figure 2.2 Illustration of the concept of value, utility, and certainty equivalent.

Decision makers who follow the rules of decision analysis (Section 2.4.2) take the alternative that maximizes expected utility.

You or an investor interested in buying your certificate may want to gather some information about the uncertain event, the outcome of tossing the thumbtack. What information would you get and how much would you pay for it? This is a "value of information" question. You may want to buy some tosses, say 50 cents per toss, or, you may want to buy a computer program that simulates tosses, and so on. All this information is, however, imperfect. It does not reveal the "truth," the ultimate toss outcome. Perfect information is tantamount to revealing the truth, here knowing the toss outcome. It makes logical sense that you would not pay more for imperfect information than for perfect information. Hence, the value of perfect information (VOPI) is an upper limit that you will never exceed when buying information. The VOPI is therefore

$$\begin{aligned}\text{VOPI} = {} & \text{value with perfect information} \\ & - \text{value without information}\end{aligned}$$

Clearly knowing the toss result will get you \$100 (=value with perfect information) and without any information you will get your CE, because that is the certain amount in your mind (knowing nothing else), hence

$$\text{VOPI} = \$100 - \text{certainty equivalent}$$

Let us now consider imperfect information or simply VOI:

$$\text{VOI} = \text{value with information} - \text{value without information}$$

Without yet getting into any calculations (these are discussed in Section 2.6.2), three main elements influence this value as per the following definitions:

1. *Prior*. What we know before, a base-level uncertainty. If we already know a lot, then additional information, data, or experiments will not add much value.
2. *Reliability*. How reliable is the information, meaning, how well it predicts what I need to know, the unknown truth.
3. *Decision*. There is no value in knowledge that does not affect the decision.

Deciding to gather information is therefore part of the decision model, in the sense that it adds one more alternative from which one can choose (see Figure 2.1). If the information gathering branch in Figure 2.1 has higher payoff, then one should decide to gather information, and then only make a decision. Note that the VOI does not depend on the cost of the information gathering. This is a common confusion. Information gathering costs are sunk costs because they precede the decision. Instead, the cost should be compared with the value of information; hence, a decision to acquire data should be made on that basis.

Imagine now that you are asked to call the toss and you made the right call. Did you make a good decision? Unfortunately, the skill of a person in terms of making decisions is often evaluated based on one outcome. Somebody got rich in life, he/she must really have made good decisions (?). But what if this outcome was purely based on chance, and whatever decision he/she made had in fact very little impact? Good decisions can be evaluated only in the long run. If one wants to compare decision making based on a gut-feeling versus decision making based on decision theory, then this can only be evaluated for a large set of decision-making processes and chance outcomes. Unfortunately, very few corporations or decision entities keep track of such success/failure rates.

2.3. CHALLENGES IN THE DECISION-MAKING PROCESS

2.3.1. The Decision Analyst

To make this section educational, the reader should now consider themselves as decision analyst/consultant observing and analyzing the decision-making process in the situations described in the following. This third-person view is important because readers may have different background and hence interpret the subjective decision process very differently, or may have been decision makers, or more likely subject matter experts. We will also illustrate the challenges with two very different situations that would be rather typical for the decision-making background in the context of this book. The first situation is a decision analyst visiting ExxonMobil in Houston (or any large oil/gas company) and the second situation concerns the Danish government (see Chapter 1 for general background information). We will abbreviate ExxonMobil as EM and the Danish government as DG. Clearly, as decision analyst and consultant, you will encounter two very different situations; hence, no single solution will fit all problems. However, in both cases you will likely interact with decision makers, stakeholders, and subject matter experts (SMEs), all of which are humans and therefore not necessarily rational. Important skills for any analyst are therefore not just technical (as most readers have) but also require certain soft skills such as understanding how people think (rational and irrational), how experts should be approached, how decision makers should or should not be aware of the technical context, how the group dynamic works, and so on. The analyst will also need to face some push-back against rational decision making or any decision-theoretic framework. Even today, with the advances in decision analysis as a science, many still rely on "my intuition" or "my gut-feeling," or "my rules of thumb." It is well documented that the rational decision-making process outperforms these one-at-a-time, anatomical decisions [*Parnell et al.*, 2013]. Few see decision analysis as something that will be beneficial in the long term, and many will judge the decision-making process on single outcomes ("see, I knew this all along, so we didn't need any technical, or advanced approaches, I could just have told you so"). That would be the same as judging one's black-jack playing skills from one single win (which is what makes casinos rich).

As decision analyst, you will not just focus on the technicalities involved in running decision models or structuring the decision axiomatically (e.g., probability theory, decision trees) but also be the facilitator integrating the complex and multiple objectives of stakeholders or the conflicting information provided by the various domain experts involved. As decision analyst, you will need to integrate technical knowledge with business knowledge. In the case of EM, you may need to have technical knowledge (such as about the subsurface). In other cases, in particularly when working with EM management, you may need to work with higher level technical managers or executives focusing on the entire decision-making process rather than on specific technical challenges. In the Danish case, you will need to be aware of the Danish democratic process, the sensitivities concerning sustainable agriculture within a changing environment, the dynamic between industry and local farmers, and the communities they live in.

2.3.2. Organizational Context

The decision-making process for EM and the DG are very different. In both the cases, however, the decision process is complex. In the case of EM, many stakeholders exist (board, stock-holders, government regulators, domain experts, executives, etc.). This is less the case for the DG which obtains some input from stakeholders, such as cities, farmers, agriculture, but because of the Danish style of democracy, the government is the central decision maker. "Stakeholders" refer to all parties with vested interest, not just decision makers or experts. A proper analysis of the stakeholders is required too since the nature of the fundamental and means objective (see Section 2.4.4) may depend on how they are defined.

Complexity is present for various reasons. First, there is the technical complexity, which the subject matter of this book. EM and also increasingly DG are using complex, multidisciplinary data acquisition and modeling approaches to inform their decisions. This by itself involves many domain experts in geology, geophysics, subsurface engineering, surface facilities, economist, and so on. With 73,500 employees (2015), EM organizational complexity is substantial. Decisions are made from the very high level to the daily operations, with a complex hierarchy, many stakeholders, contractors, and experts. Typically, various decision levels are present. Strategic decisions focus on the long-term goals of the organization: the "mission." Tactical decisions turn these strategic goals into measurable objectives. This book covers some of these types of decisions, such as how to allocate resources (cleaning, drilling, data acquisition) to obtain certain objectives. Day-to-day operational decisions are short term and usually reactive. The latter usually does not involve complex modeling or technical analysis.

Therefore, it is important for the decision analyst to understand the social aspect of such organizations, in particular the cultural differences that exist in these various situations. For DG, EM, and others, no single solution fits all. In fact, it may be dangerous to think of solutions, because it points to an overly technical and analytical approach to the problem, ignoring the human aspect. Public sectors often require transparency and clear oversight, while private companies, certainly those not publicly traded, may have a very closed decision-making process.

One of the common issues, certainly in large organizations is the lack of transparency around objectives; this leads to technical experts to perform their technical work without proper context. They have no stake in the decision but simply execute some task. This may lead to gathering data without real goals, or ambiguous goals, or just collect data because "that's what we always do." As such, technical experts may focus on a wrong problem or an unimportant problem or task.

In executing such tasks, there may be overconfidence in one's judgment, or overreliance on the limited domain of expertise. This is common in oil/gas companies. The domain expert will emphasize that their domain is important and relevant, "because it is." Some geophysicist may state that everything can be explained with geophysical data, or well-test engineers with his/her well-test data, as long as enough time is spent on analyzing the data or gathering more "perfect data." From a human point of view, this is understandable, since the domain expert may have anxiety about one's irrelevance with the larger context of the problem; hence, the focus is on the narrow problem only. This way of working often leads to some form of "decision paralysis," meaning postponing decisions until everything is fully understood (determinism). The problem is that in any sciences and in particular in the subsurface geological sciences, we will rarely fully understand everything; hence, geologist may find it difficult to move forward. This also makes their domain increasingly irrelevant, since usually some form of quantification is needed to make decisions meaningful.

Another issue, in particular in large organization, is that both the decision analysis and the domain experts are shielded from the decision maker. In fact, there is often a geographical problem as decision makers do not work in the same location (or even building) as the technical experts. As such, experts rarely understand the decision maker's preferences and therefore lack value-focused thinking (addressing their own small problems, instead of the organizations').

Cognitive bias is a problem when dealing with complex situations. "Cognitive biases are mental errors caused by our simplified information processing strategies. A cognitive bias is a mental error that is consistent and predictable" [*Heuer*, 1999]. A typical problem in both academia and industrial setting-related decision problems is the bandwagon effect, meaning doing things a certain way because that is what other people do, without asking questions as to whether this is appropriate. This bandwagon effect may be present on a small scale, such as experts always using a software in the same way, without question, because that is what the organization does or that is what the software provides, even if it makes no sense. At a larger scale, a bandwagon effect may affect entire industries or academic fields. In Chapter 5, we will discuss this extensively as "blindly following the paradigm." In this type of bandwagon effect, there is an undocumented consensus that things should be done in a certain way, and that any other way that questions on the very nature of the paradigm is simply cast aside (and hence never funded!).

Information and confirmation biases occur when information is gathered without knowing if it adds value or worsens it, to confirm a hypothesis rather than attempting to reject one (see Chapter 5 on inductionism vs. falsificationism). Another common trait is to anchor, meaning creating a best guess and anchoring uncertainty on that best guess, never questioning the anchor. In the subsurface, this is quite common. For example, a few wells are drilled, the average of some petrophysical property is estimated from logging or coring, and the uncertainty on that property is specified as the mean of the data plus or minus some standard deviation. Clearly, the mean may be completely incorrect, due to under-sampling, biases, measurement issues, and so on. Another common form of anchoring is to build a base case and design the entire future on it even in the presence of evidence that refutes the base case, or to make ad hoc modification to the base case. The issue of ignoring Bayes' rule and making ad hoc model choices, without assessing them against evidence, or evaluating the probability of such ad hoc modification, will be treated in extenso in Chapter 5.

2.4. DECISION ANALYSIS AS A SCIENCE

2.4.1. Why Decision Analysis Is a Science

What is science? This common question is also known as the "demarcation problem," first introduced by *Popper* [1959]. Science operates in certain ways; a complex interaction of axioms, hypothesis, conjectures, evidence gathering, experimentation, ways of reasoning, such as induction and deduction, and others such a Bayesianism. We will dedicate Chapter 5 to this topic.

Decision analysis uses axioms of probability theory and utility theory [*Howard*, 1968; *Raiffa*, 1968; *Keeney and Raiffa*, 1993]. Most decision analysis are Bayesian (see Chapter 5) in the sense that they work with subjective beliefs and Bayes' rule to update such beliefs with evidence. They accept the notion of conditional probability in doing so. In addition to these axioms, decision analysis relies on behavioral decision theory, an area of psychology [*Edwards*, 1954; *Kahneman et al.*, 1974]. For example, prospect theory (winning the Noble Prize in 2002) uses behavioral decision theory as an alternative to the well-known utility theory. Game theory is another important element in decision science [*Von Neumann and Morgenstern*, 1944].

2.4.2. Basic Rules

Decision analysis guides the decision maker to turn opaque situations into a clear set of actions based on beliefs and preferences. Therefore, it is both prescriptive and normative. The latter require invoking a set of rules/axioms. We already encountered one rule of decision analysis in the thumbtack example: maximize expected utility.

Parnell et al. [2013] state five basic rules under which any decision analysis should operate. They are as follows:

1. *Probability rule*. A formulation of subjective degrees of belief. Decision analysis is Bayesian and requires exhaustive and mutually exclusive events.
2. *Order rule*. It refers to the order of preferences for all prospects, such ordering also needs to be transitive: if you prefer X over Y and you prefer Y over Z, then you must prefer X over Z.
3. *Equivalence rule*. It refers to the hypothetical creation of a lottery involving the best and the worst prospects. Suppose there are three prospects X, Y, and Z. X is the worst, and Z is the best. Some probability p exists such that a deal gives you X with probability p, Z with probability $(1 - p)$, and you are receiving Y for sure (CE). This probability p is termed "the preference probability" because it depends on preferences rather than referring to real events.
4. *Substitution rule*. The decision maker should be willing to substitute any prospect with a lottery. In other words, your preference for a prospect will not change if an uncertain deal contained in the prospect is replaced by the CE.
5. *Choice rule*. The decision maker should choose the lottery with the highest probability of winning (i.e., a Bayesian classification). Simply if you prefer prospect X over Y, and if in deal A, $P(X) = 35\%$ and in deal B $P(X) = 20\%$, then you prefer deal A.

2.4.3. Definitions

As with any science, decision analysis operates with definitions and nomenclature. This will help with a clear structuring of the decision problem and with identifying the main "elements" and avoid any ambiguity.

Important to making a decision is to define the *decision context*, that is, the setting in which the decision occurs. Note that the same decision problem may occur in different contexts. The context will identify relevant alternatives and set the objectives. The context will also identify the decision maker, that is, that person whose objectives and preferences are required. In the context, the necessary assumptions and constraints need to be identified as well.

Decision: A conscious, irrevocable allocation of resources to achieve desired objectives. A good decision is, therefore, an action we take that is logically consistent with the objectives stated, the *alternatives* we believe there to be, the knowledge/information, datasets, and the preferences we have. Decision making is not possible if there are no (mutually exclusive) alternatives or choices to be decided on. Alternatives can range from the simple yes/no (e.g., cleanup or not), through the complex and sequential (e.g., oil and gas exploration, field development), to those with extremely large numbers of alternatives. Leaving out realistic alternatives has been identified as a fatal flaw, in hindsight, in important decisions. A decision is only as good as the alternative listed.

Rational decision making requires clear *objectives* that will be used to compare each alternative. An *objective* is defined as a specific goal whose achievement is desired.

A quantitative measure to determine how well each alternative achieves the stated objective is needed. This measure is often termed an *attribute*. A *payoff* or *performance score* is what finally happens with respect to an objective, as measured on its value scale, after all decisions have been made and all outcomes of uncertain events have been resolved. Payoffs may not be known exactly because of uncertainty and need to be predicted.

A value metric is then a quantitative scale that measures the value to the decision makers of the degree to which objectives are achieved. *Value functions* map performance scores to a value metric.

The following are the other common definitions:

1. *Risk preference*. A description of a decision maker's attitude toward risk, whether averse (EM), neutral (DG), or seeking.
2. *Utility metric*. It is a quantitative scale that expresses the decision maker's attitudes toward risk-taking for the value metric.
3. *Utility function*. It maps the utility metric to a value metric in the case of a single-dimensional utility function. Section 2.4.5 will provide an example to illustrate these various definitions.

2.4.4. Objectives

Decision problems may have a single objective (e.g., maximize share-holder value) or multiple, often competing objectives (maximize income, minimize environmental impact). In single objective cases, a common performance score is net present value (NPV). Monetary scales are often preferred as dollar values allow for easier comparison. Another common and easily interpretable scale is "time." Value functions are used to translate any nonmonetary performance score into a monetary value metric (see Section 2.4.5.2 for example). Single objective decisions also allow for risk-attitude in terms of single-dimensional utility functions. These functions need to be assessed by interviewing the decision maker. In risk-neutral cases, the expected value is maximized.

Many problems involve multiple objectives (see, e.g., the Danish groundwater case of Chapter 1). These objectives are organized using a value tree. This tree is generally developed by working from high-level to specific objectives. "Values" are general in nature: for example, values could be "be popular," "support UNICEF," "be healthy," "make money," while objectives are specific and could be of the form "maximize this" or "minimize that." One should distinguish between fundamental objectives that identify the basic reasons why a decision is important and means objectives that are ways of achieving a fundamental objective. Fundamental objectives should be independent and can be organized in a hierarchy. For example, "maximize profit" can be divided into "minimize cost" and "maximize revenue." Means objectives are not the fundamental reason for making a decision; a means objective could be, for example, to "create a clean environment" or to "have welfare programs." Indeed, welfare programs and a clean environment are only a means to population happiness. Figure 2.3 shows such a tree that could be relevant to a local government. Some objectives are fundamental (improve welfare), others are means (improve safety).

The next step is to measure the achievement of an objective. For certain objectives, there will be a natural scale, in either dollars or ppm or rates. For other, more descriptive objectives, a scale needs to be constructed, usually through numerical or other "levels" (high, medium, low). An objective such as "minimize tax" has a natural scale in dollars, while others such as "maximize ecosystem protection" can be measured using the constructed scale:

1 = no protection
2 = minimal monitoring
3 = monitoring/reactive
4 = monitoring/proactive
5 = special status as protected zone

2.4.5. Illustrative Example

2.4.5.1. Overview. Chapter 8 presents a real-life example of the above-mentioned ideas. Here we discuss a simple hypothetical case that will help clarify some of the concepts and definitions.

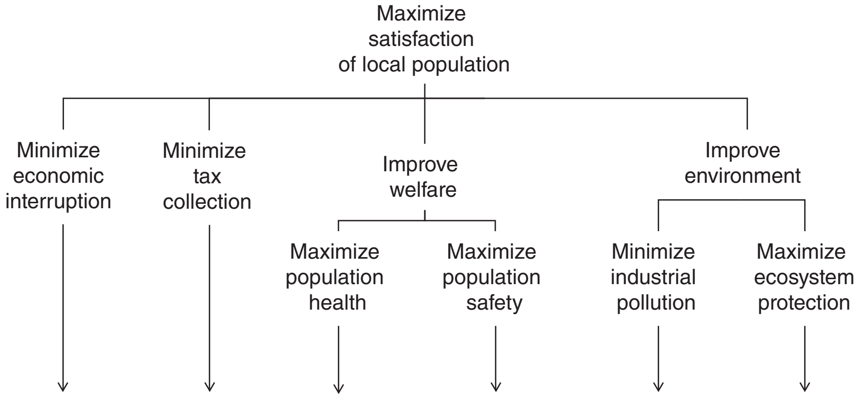

Figure 2.3 Example of a hierarchical tree with objectives.

Consider that in Denmark a leakage of chemicals was discovered in the subsurface close to an aquifer. Government analysts in collaboration with consultants are speculating that due to the geological nature of the subsurface, this pollution may travel to the aquifer and potentially be widely distributed. Models built on gathered data (e.g., SkyTEM) can be used to make any probabilistic forecasts of a property of interest.

The local government has to make a decision, which in this case is whether to act, and hence start a cleanup operation (which is costly for tax-payers) or do nothing, thereby avoiding the cleanup cost but potentially be asked to pay damages to local residents in case widespread contamination occurs. What decision would the local government make? Cleanup or not? How would they reach such a decision? Are there any other alternatives? For example, monitoring at certain locations, cleaning if contamination is detected, or importing "clean" water from another source? Is investing in such monitoring actually useful?

2.4.5.2. Performance Score Matrix. Recall that a performance score is a metric that quantifies how an objective is met after the decision is made and the outcomes of any uncertain events have been resolved. Therefore, performance scores are not known in advance and must be predicted. This is what most of this book is about. The objectives are listed in the tree of Figure 2.3 and the alternatives are whether to "cleanup" or "not cleanup." Assuming neither alternative will impact safety (cleaning up or not will not affect crime), then Table 2.1 could be an example of hypothetical performance scores matrix (also called payoff matrix) for this case. These are averages (expected values) which would be fine if the decision maker is risk neutral (a Scandinavian government may be more risk averse). In reality, probability density functions are obtained from the modeling study.

Tax collection will be impacted by such cleanup because of its cost (say $10 millions), which will affect the local budget. Ecosystem protection will increase (a constructed scale), while industrial pollution (in ppm) will be small (some pollutants may be left in the ground). In the case of not cleaning up, the tax collection also increases because of the requirement to import "clean" water to meet the needs of the population, assuming the government would have to pay for this (e.g., suppose the contamination was made by a government research lab). This number is more difficult to establish. Indeed, damage payoffs will occur when the geology is unfavorable or if the pollutant is very mobile in the specific environment, causing the pollution to leak into the aquifer. In a payoff matrix, it makes sense to only include objectives that distinguish among alternatives. Any other objectives should be removed, such as population safety in this case. Also, in a payoff matrix, one works across the rows of the payoff matrix rather than down its columns.

Table 2.1 Hypothetical performance score matrix in a binary decision problem.

		Alternatives	
		Cleanup	Do not cleanup
Objectives	Tax collection (million $)	10	18
	Industrial pollution (ppm/area)	30	500
	Ecosystem protection (1–5)	4	1
	Population health (1–5)	5	2
	Economic interruption (days)	365	0

The next evident question is how to incorporate preferences into a single attribute scale and combine performance scores measured on different scales. This is addressed by the above-mentioned value functions. Value functions transform attributes to a common scale, say, from 0 to 100. The value function expresses how an increase in the score translates into an increase in value. Therefore, a linear value function (Figure 2.4) states that such an increase is proportional, such as for health, or inversely proportional, such as for pollution. A nonlinear function such as for taxes in Figure 2.4 states that an increase in dollars collected results in a smaller decrease in actual value (high value if less taxes are collected). This means that if tax becomes larger, then any increase in tax will leave the population not necessarily equally more displeased (low value); they are already displeased with such high taxes! For the ecosystem, one could argue for an opposite attitude: more pollution will eventually completely ruin the ecosystem, while a small increase can possibly be tolerable. Such nonlinearity in the function can therefore be interpreted as the attitude toward "risk" one may have about certain outcomes. For example, the attitude toward safety may be different than the attitude toward income. One's preference may be to risk more when money is involved (tax) than with the environment because such effects are often irrevocable (although governmental attitudes around the world may substantially vary in this aspect).

2.4.5.3. Swing Weighting. Different objectives may carry different weights. This allows the decision maker to inject his/her preference of one objective into another. For example, preference in environmental protection may supersede preference in being displeased with increased taxes. Note that preference is used here to compare

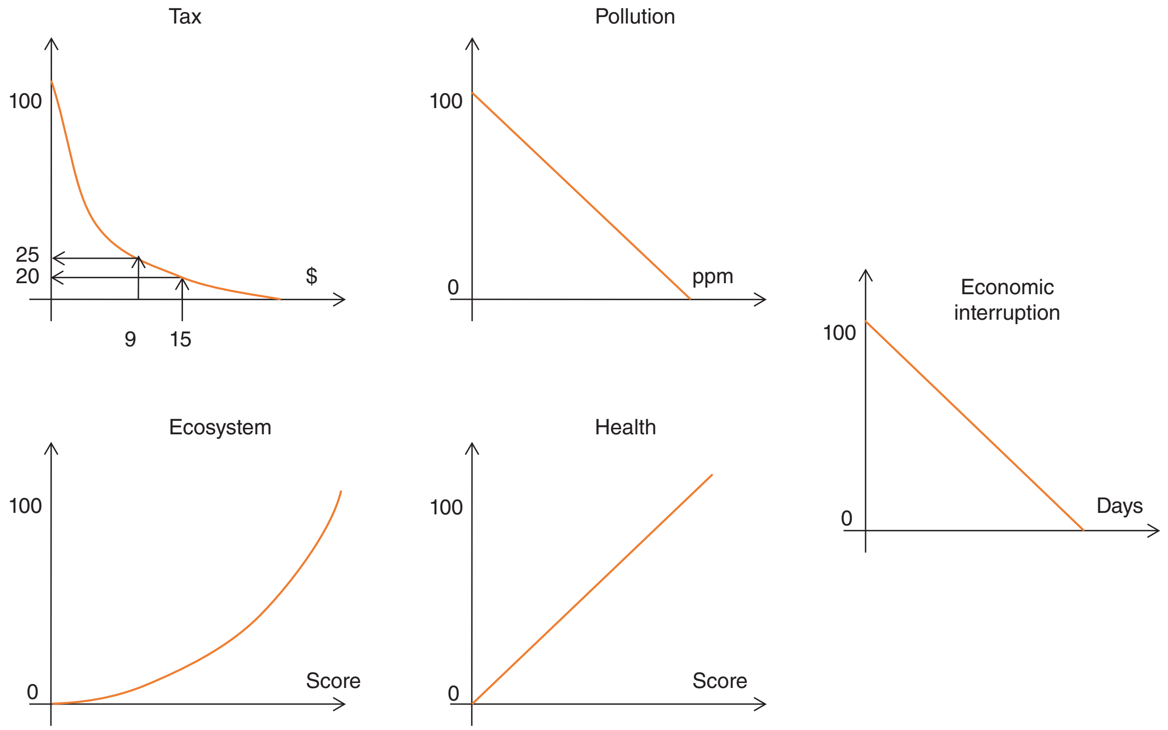

Figure 2.4 Hypothetical value functions, turning a score into a common scale.

various objectives, which is different from the previous sections where preference was used to describe "risk" toward various outcomes within a single objective. One may be tempted to use a simple relative weighting using the following: (i) Rank the various objectives, (ii) assign a number on scale 0–100, and (iii) normalize and standardize the score to unity.

Such an approach does not account for the performance scores on the alternatives. For example, a specific objective may be ranked high but may not have much effect on the various alternatives formulated. A direct weighting method, therefore, does not account for the ultimate purpose, that is, to decide among various alternatives. In practice, the problem can be overcome by using swing weighting, which considers the relative magnitudes of the performance scores. The objectives are first ranked by considering two hypothetical alternatives: one consisting of the worst possible payoff on all objectives (in terms of score, not value) and one consisting of the best possible payoff. The objective whose best score represents the greatest percentage gain over its worst score is given the best rank (i), and the methodology is repeated for the remaining objectives until all are ranked.

Since we are dealing with a binary decision problem, the weighting problem does not present itself (there is always a best and a worst). To illustrate the swing weighting, therefore, consider a slightly modified example where one adds two more alternatives: (i) a detailed cleanup that is costlier but removes more contaminant, therefore, protecting health and environment and (ii) a partial cleanup that leaves some pollutant behind with a decreased risk of drinking water contamination. Table 2.2 shows how swing weighting works. First, the best and worst scores for each objective are taken, then the relative differences are ranked, with 1 being the largest relative difference. Clearly, the tax impact is least discriminating amongst the alternative and therefore gets the smallest weight. Weights are then attributed to each objective following the rank order and then normalized. After weights and attributes are defined, we can combine scores on each objective to determine an overall value for each alternative. This is achieved by calculating the weighted sum of each column in the matrix:

$$v_j = \sum_{i=1}^{N_j} w_i v_{ij} \qquad (2.1)$$

where w_i is the weight calculated for each objective and v_{ij} is the score of the j-th alternative for the i-th objective. This is done in Table 2.3 where attributes are now turned into values using some hypothetical value functions (not shown). Therefore, in summary, the cleanup alternative

Table 2.2 Calculating swing ranks.

Alternatives

Objectives	Detailed cleanup	Cleanup	Partial cleanup	Do not cleanup	Best	Worst	Swing rank
Tax collection (million $)	12	10	8	18	8	18	5
Industrial pollution (ppm/area)	25	30	200	500	25	500	2
Ecosystem protection (1–5)	5	4	2	1	5	1	3
Population health (1–5)	5	5	2	2	5	2	4
Economic interruption (days)	500	365	50	0	500	0	1

Table 2.3 Outcome of the hypothetical score matrix with cleanup being the winning alternative.

Objectives	Rank	Weight	Detailed cleanup	Cleanup	Partial cleanup	Do not cleanup	Type
Tax collection (million $)	5	0.07	30	20	100	0	Return/$ benefit
Industrial pollution (ppm/area)	2	0.27	100	99	40	0	Risk/$ cost
Ecosystem protection (1–5)	3	0.20	100	75	25	0	Risk/$ cost
Population health (1–5)	4	0.13	100	100	0	0	Risk/$ cost
Economic interruption (days)	1	0.33	0	33	90	100	Return/$ benefit
		Total	62.1	**67.0**	52.5	33.0	
	Return/$ benefit		2.1	12.3	36.7	33	
	Risk/$ cost		60	54.7	15.8	0	

Note: Calculation of risk versus return.

is the one that is logically consistent with maximizing the value of the decision, for given alternatives, objectives, weights, score predictions, and preferences expressed in value functions.

2.4.5.4. The Efficient Frontier. Conflicting objectives can make decision making hard. In this case the minimization of tax burden is opposite to the cost of maintaining a clean environment. Increasing returns (money) may come at the expense of increasing risks (health, safety, and environment). A term called "the efficient frontier" may help investigate what kind of trade-offs are made and possibly change a decision based on this insight. This is very common in portfolio management (choice of equities, i.e., shares in stocks of companies, and bonds). Portfolio management utilizes historical data on return of equities to form the basis for assessment or risk and return and use the past performance as a proxy for future performance.

To study trade-offs, two categories are created: one for the risks and one for the returns (or cost/benefit). Overall weighted scores are then calculated for each subset, in a similar fashion as described earlier, as shown in Table 2.3. Risk/return is plotted versus cost/benefit in Figure 2.5. From this plot, we can eliminate some obvious alternatives as follows. The alternative "do not cleanup" is clearly dominated by the alternative "partial cleanup." Indeed, "partial cleanup" has both more return and less risk. Therefore, the alternative "do not cleanup" can be eliminated because it results in taking on more risk relative to the return. "Do not cleanup" is the only alternative that can be eliminated as such; other alternatives involve a trade-off between risk and return. The curve connecting these points is the efficient frontier. The efficient frontier can be seen as the best set of trade-offs between risk and return for the current alternatives. Recall that a decision can only be as good as the alternatives formulated. Therefore, pushing the efficient frontier upward (i.e., up and toward the right in Figure 2.5) would require different alternatives, leading to a better set of trade-offs. Such alternatives are only as good as the imagination of those creating them.

An efficient frontier allows asking question such as "Am I willing to trade-off more risk for more return between any two alternatives?" For example, is the decrease of about five units of risk, worth the decrease

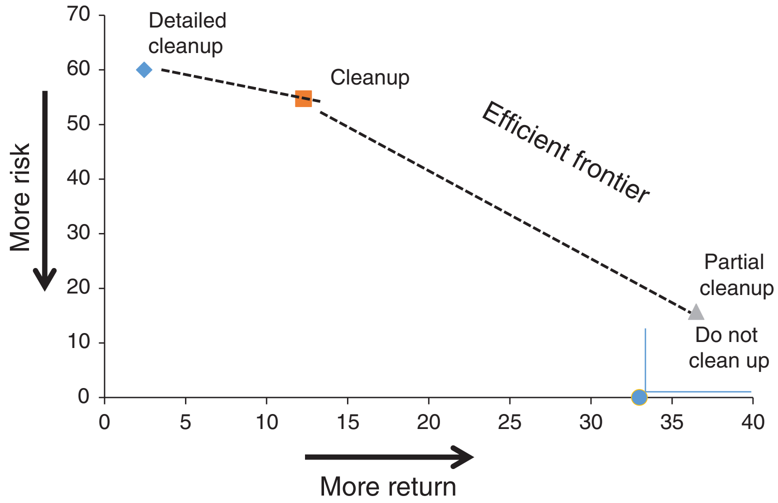

Figure 2.5 Efficient frontier.

in about ten units of return when going from detailed cleanup to "cleanup"? If all attributes were in dollar values than these would be actual dollar trade-offs, in our case these are only indicative trade-offs, basically forming a scale from "less preferred" to "more preferred" in terms of trade-off.

2.5. GRAPHICAL TOOLS

2.5.1. Decision Trees

Decision trees (Figure 2.6) are graphical models that organize logically, in time, the various decisions, alternatives, uncertainties, and payoffs (value for each prospect). The time component is critical here. First, we state the alternatives, then we face uncertainties (not the other way around); these uncertainties are then resolved sometime in the future, resulting in a payoff. This also means that the root is a decision. Any costs or uncertainties prior to the decision are irrelevant. The leaves in the decision tree represent the various scenarios that can occur.

To solve a decision tree, meaning find the best alternatives, we go the opposite way: we start at the leaves and resolve uncertainty nodes by taking consecutively expected values. If the decision maker is not risk neutral, then the solution involves utilities. At any decision nodes, we then take the alternative that is maximal (maximum expected utility). Figure 2.6 shows a hypothetical example. Some of the probabilities in this tree are prior probabilities, other may be the result of modeling (conditional probabilities).

A limitation of decision trees is that they become intractable for decisions with either a large set of alternatives or a more continuous type of uncertainty, rather than discrete outcomes such as in Figure 2.6.

2.5.2. Influence Diagrams

An influence diagram captures a decision situation by depicting relationships between decisions, uncertainties, and preferences [*Shachter*, 1986; *Eidsvik et al.*, 2015]. Consider as illustration the hypothetical example in Figure 2.7. A site is contaminated, which potentially poses a health risk. The decision is to clean (or not, or how to clean) and also the decision is to hire a consultant (or not). Depending on a report (negative/positive) certain actions will be taken. The outcome of the report depends on the unknown distribution of the subsurface plume. The costs will depend on how uncertainties are resolved. One distinguishes three kinds of nodes (uncertain nodes, decision nodes, and value nodes) and three kinds of arcs (conditional, information, and functional). Notice how there is no arc between "clean" and "contamination." The decision to clean does not affect the amount of contamination present before cleaning. Each uncertain node is associated with a probability table. For example, the contamination node can be associated with a table of "low," "medium," and "high" contamination and associated probabilities (obtained through measurements and models). A value node is associated with a value table indicating the payoffs of various scenarios. In that sense, calculations can be done with influence diagrams in the same way as with decision trees. Because the time component is not explicitly represented, it is easier to make mistakes with such diagrams, in particular when they become complex (e.g., Figure 2.8). For example, information should be

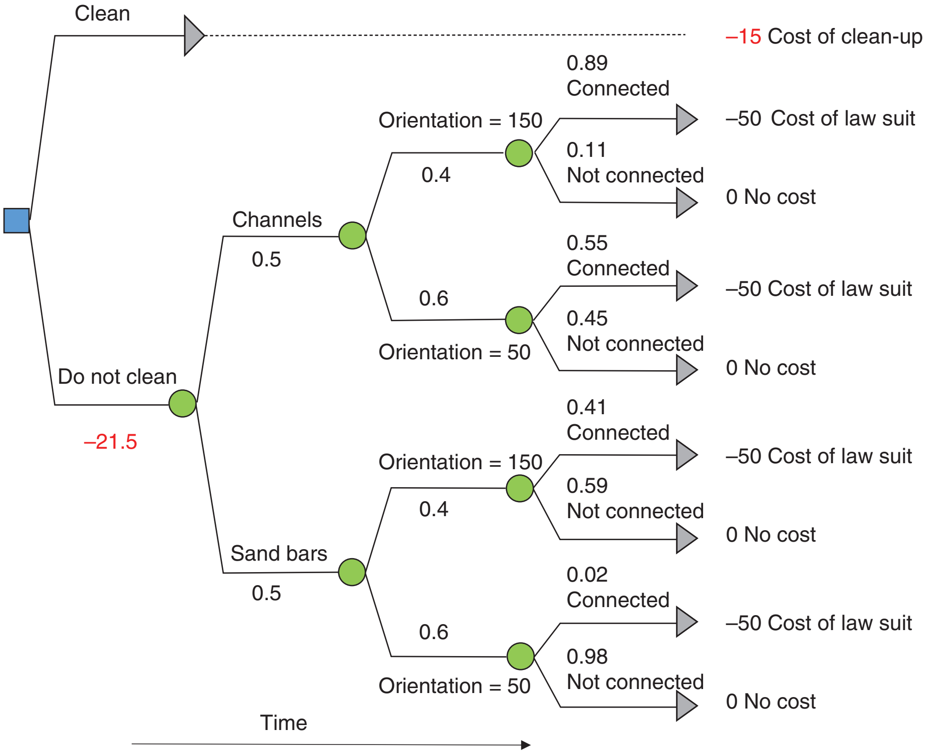

Figure 2.6 A hypothetical decision tree. The first node has to be a decision node. Uncertainties here are the type of geological system (channel vs. bar), the orientation of geological bodies and the degree of connectivity between them as measured by a probability. The latter is calculated from actual models. The best alternative is "clean." Adapted from *Caers* [2011].

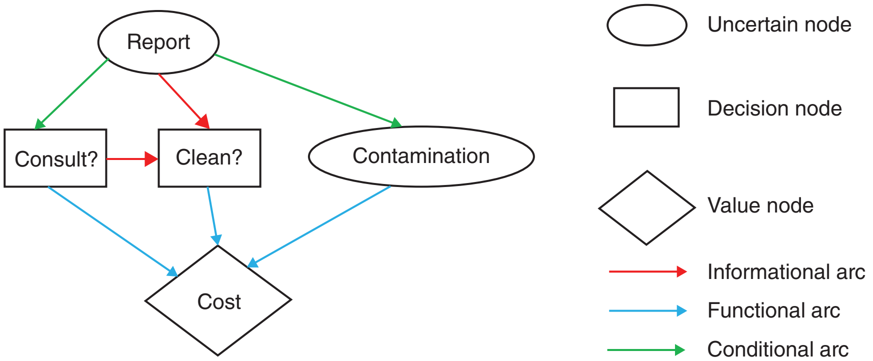

Figure 2.7 Example of a hypothetical influence diagram.

known to all decisions that are posterior to the information acquisition. It is not rational to forget information.

2.6. VALUE OF INFORMATION

2.6.1. Introduction

In many practical situations, we are faced with the following question: Given a decision situation between several alternatives, do we choose or do we decide first to gather information to help improve the decision? In the subsurface, this may mean many things: conducting a geophysical survey, drilling wells, doing more core experiments, doing a more detailed modeling study, hiring experts or consultant, and so on. The main driver is to reduce uncertainty on key decision variables. However, data acquisition may be costly. Questions that arise include the following:

1. Is the expected uncertainty reduction worth its cost?
2. If there are several potential sources of information, which one is the most valuable?

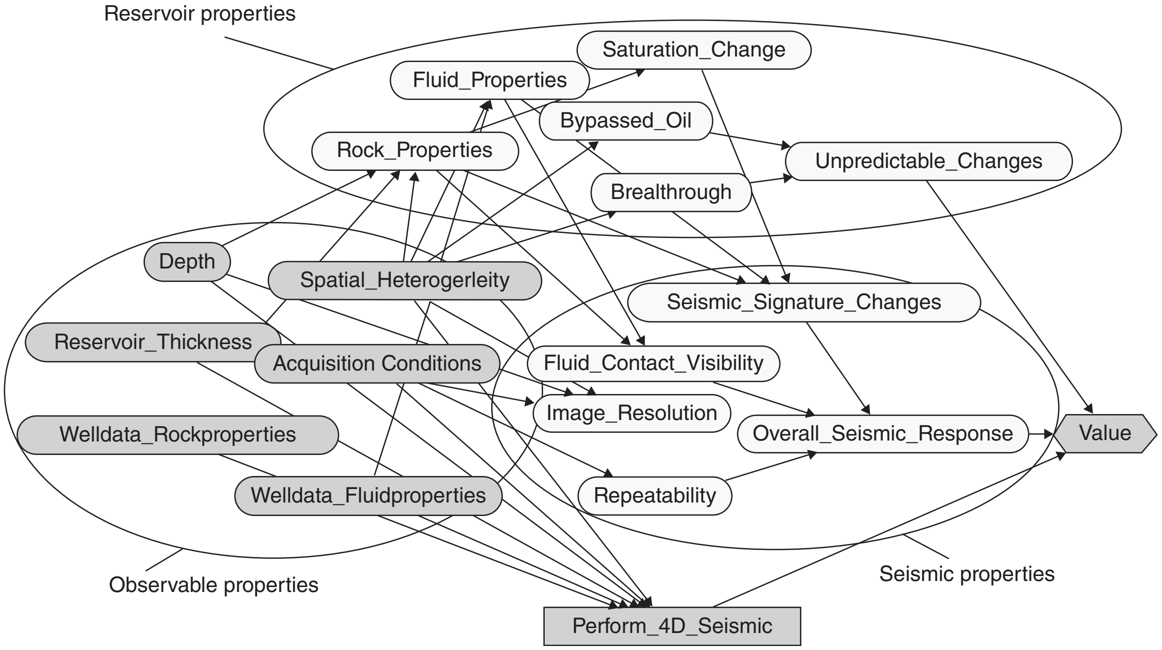

Figure 2.8 Example of a complex influence diagram for assessing the value of 4D seismic data. From *Eidsvik et al.* [2015].

3. Which sequence of information sources is optimal?

These types of questions are framed under "the value of information problem." These questions are not trivial to answer because we need to assess the value *before* any measurement is taken. You cannot first take the measurement and then decide whether it is valuable, because then you have already decided to invest in some sunk cost.

Decision analysis and VOI has been widely applied to decisions involving engineering designs and tests, such as assessing the risk of failure for buildings in earthquakes, components of the space shuttle, and offshore oil platforms. In those fields, gathering information consists in doing more "tests" and if those tests are useful, that is they reveal design flaws (or lack thereof), then such information may be valuable depending on the decision goal. This invokes some measure of "usefulness" of the test. Indeed, if the test conducted does not inform the decision variable of interest, then there is no point in conducting it. The "degree of usefulness" is termed the "reliability" of the test in the traditional value of information literature. In engineering sciences, the statistics on the accuracy of the tests or information sources that attempt to predict the performance of these designs or components are available, as they are typically made repeatedly in controlled environments such as a laboratory or testing facility. These statistics are required to complete a VOI calculation as they provide a probabilistic relationship between the information message (the data) and the state variables of the decision (the specifications of the engineering design or component).

Many challenges exist in applying this framework to spatial decisions pertaining to an unknown subsurface. *Eidsvik et al.* [2015] provide a thorough treatment on the topic including several case studies. For application to petroleum system in particular, see *Bratvold et al.* [2013]. Here we provide a short overview of the main elements.

2.6.2. Calculations

The aim of collecting more data is to reduce uncertainty on those parameters that are influential to the decision-making process. In the thumbtack example, we discussed that VOI should depend on three components:

1. The prior uncertainty of what one is trying to model. The more uncertain one is about some subsurface component the more the data can possibly contribute to resolving that uncertainty.

2. The information content of the data (this will be translated into data reliability or vice versa). If the data is uninformative, it will have no value. But even perfect data (data that resolves all uncertainty) may not help if that does not influence the decision question.

3. The decision problem. This drives the value assessment on which any VOI calculation is based.

The simplest way to illustrate VOI calculation is by means of a decision tree. Consider again, our simple illustrative "contamination" case. The top part of the tree in Figure 2.9 is the basic decision problem. It is binary and has one binary uncertainty: contamination is low (a_1)

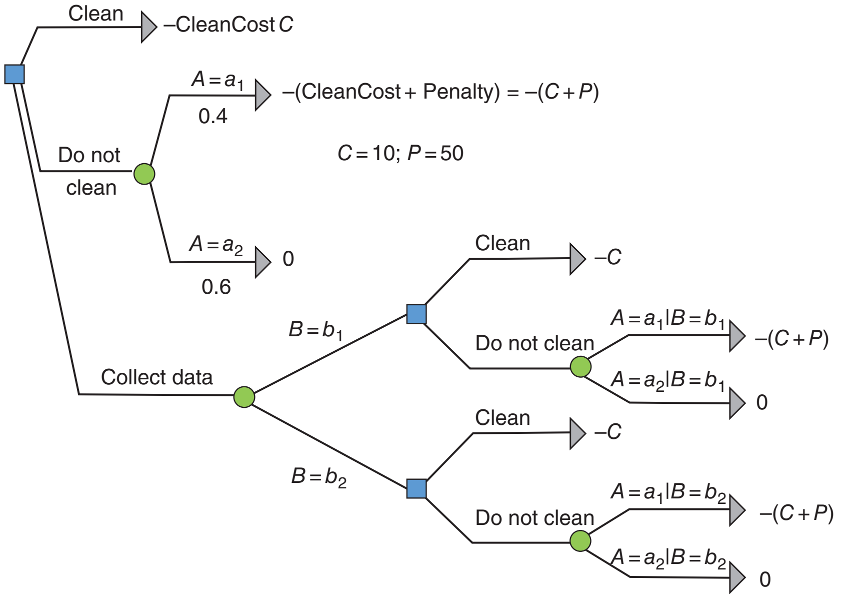

Figure 2.9 Example of a decision tree that involves collecting data as an alternative.

versus contamination is high (a_2). In VOI assessment, we consider acquiring data as an additional alternative. However, now we also face an additional uncertainty: What is the outcome of this data acquisition? Here we consider a binary outcome: positive versus negative. Positive means *indicating* "high contamination" (b_2) and negative means indicating "low contamination" (b_1). The term "indicating" is important here: we do not know for sure; the data may not necessarily be clairvoyant and reveal the truth. Next we notice in the tree that the basic decision problem is literally repeated after each possible data outcome. This is important. If this is not done properly then VOI may be negative, which makes no sense because you can always decide not to gather information. Instead, what has changed is the probability associated to the branches involving our uncertainty. We now have a conditional probability instead of a prior probability. The conditional probability $P(A_i = a_i | B_j = b_j)$ is termed the information content and is of the general form P(real world is| data says). In traditional VOI calculations, and we refer here to the original engineering test, the following probability is usually specified P(data says| real world is). This originated from the idea of doing tests under various "real world" conditions. The relationship between information content and reliability is simply Bayes' rule.

Let us assume perfect information, meaning that

$$P(A_1 = a_1 | B_1 = b_1) = 1; P(A_1 = a_1 | B_2 = b_2) = 0; \\ P(A_2 = a_2 | B_1 = b_1) = 0; P(A_2 = a_2 | B_2 = b_2) = 1 \qquad (2.2)$$

The data is clairvoyant, that is, it will tell if we have low or high amount of contaminant. Considering the numbers in Figure 2.9, we find that for the basic decision problem "clean" has value −10 and "not clean" has value −7. If we have perfect information, then the "collect data" branch has value −4. Hence, the VOPI is −4 − (−10) = 6 in other works (assuming number in $K), we would never pay more than $6000 for any information. Plugging in any other values will result in the VOI. These reliabilities require modeling studies. It would require forward modeling of the data on some reference cases (or using Monte Carlo) and observing how well the data resolves the truth.

REFERENCES

Bratvold, R. B., and S. H. Begg (2010), *Making Good Decisions*, Society of Petroleum Engineers, Richardson, TX.

Bratvold, R. B., J. E. Bickel, and H. P. Lohne (2013), Value of information in the oil and gas industry: Past, present, and future, *SPE Reserv. Eval. Eng.*, *12*(4), 630–638, doi:10.2118/110378-PA.

Caers, J. (2011), *Modeling Uncertainty in the Earth Sciences*. Wiley, Hoboken, NJ.

Edwards, W. (1954), The theory of decision making, *Psychol. Bull.*, *51*(4), 380–417, doi:10.1037/h0053870.

Eidsvik, J., T. Mukerji, and D. Bhattacharyya (2015), *Value of Information in the Earth Sciences: Integrating Spatial Modeling and Decision Analysis*, Cambridge University Press, Cambridge.

Heuer, R. J. (1999), Improving intelligence analysis, in *Psychology of Intelligence*, edited by J. Davis, CIA, Washington, D.C., pp. 173.

Howard, R. A. (1966), Information value theory, *IEEE Trans. Syst. Sci. Cybern.*, *2*(1), 22–26, doi:10.1109/TSSC.1966.300074.

Howard, R. A. (1968), The foundations of decision analysis revisited, *IEEE Trans. Syst. Sci. Cybern.*, *4*(3), 211–219, doi:10.1017/CBO9780511611308.004.

Howard, R. A., and A. E. Abbas (2015). *Foundation of Decision Analysis*, Pearson, London.

Kahneman, D., P. Slovic, and A. Tversky (1974), Judgment under uncertainty: Heuristics and biases, *Science*, *185*(4157), 1124–1131, doi:10.1126/science.185.4157.1124.

Keeney, R., and H. Raiffa (1993), Decisions with multiple objectives–preferences and value tradeoffs, *Behav. Sci.*, *39*, doi:10.1002/bs.3830390206.

Parnell, G. S., T. A. Bresnick, S. N. Tani, and E. R. Johnson (2013). *Handbook of Decision Analysis*, Wiley, Hoboken, NJ, doi:10.1002/9781118515853.

Popper, K. R. (1959), The logic of scientific discovery. *Phys. Today*, *12*(11), 53, doi:10.1063/1.3060577.

Raiffa, H. (1968), Decision analysis: Introductory lectures on choices under uncertainty, *MD Comput.*, *10*(5), 312–328.

Shachter, R. D. (1986), Evaluating influence diagrams, *Oper. Res.*, *34*(6), 871–882, doi:10.1287/opre.34.6.871.

Von Neumann, J., and O. Morgenstern (1944), *Theory of Games and Economic Behavior*, Princeton University Press, pp. 625, doi:10.1177/1468795X06065810.