Uncertainty Analysis in Reservoir Characterization and Management: How Much Should We Know About What We Don’t Know?

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ABSTRACT

A reservoir is the result of geologic processes and is not randomly generated. However, many uncertainties exist in reservoir characterization because of subsurface complexity and limited data. Uncertainties can be mitigated by gaining more information and/or using better science and technology. How much uncertainties should be mitigated depends on the needs of decision analysis for reservoir management and the cost of information. Uncertainty analysis should be conducted for investigational analyses and for decision analysis under uncertainty and risk. To know what needs to be known and what can be known should be the main focal points of uncertainty analysis in reservoir characterization and management.

INTRODUCTION

No uncertainty exists in a reservoir, only uncertainty in our understanding and description of it. A reservoir is not random; it was deposited geologically and evolved into a unique hydrocarbon-bearing entity. Matheron (1989, p. 4) once remarked “Randomness is in no way a uniquely defined or even definable property of the phenomenon itself. It is only a characteristic of the model.” If a reservoir is not random, why should we use a probabilistic method to build a reservoir model? If a reservoir is deterministic in nature, why should we analyze uncertainties in reservoir characterization?

Before answering these questions, it is useful to briefly review the history of uncertainty analysis and two doctrines regarding the course of nature in other scientific fields. Many consider that, historically, probability as a measure of uncertainty was first introduced by monks at the Port-Royal monastery in Paris (Arnauld and Nicole, 1662), although this may not be universally agreed on. The uncertainty notion in their exemplary argument, that fear of harm should be proportional to the probability of an event inspired the development of the probability theory for uncertainty analysis, which in the beginning was applied mostly in games of chance. Uncertainty analysis was largely ignored in the scientific world until the advent of quantum mechanics, which revolutionized physics in the 20th century. Although nearly all physical sciences were traditionally considered deterministic, many phenomena in quantum mechanics could not be explained by Newtonian deterministic laws (Popper, 1979; Hilgevoord and Uffink,
As a result, indeterminism and uncertainty analysis (initially commonly referred to as uncertainty principle) were proposed by several prominent physicists in the late 1920s. The debate centered on whether the world was indeterministic or whether quantum mechanics simply provided an incomplete description of a fully deterministic world. This is now referred to as the "EPR paradox" (Honderich, 2005, p. 237), after the initials of Einstein, Podolsky, and Rosen, who related "randomness" and uncertainty in quantum mechanics to one's ignorance or inability to fully understand or describe some properties of reality (Einstein et al., 1935). This is very similar to reservoir descriptions. Is a reservoir random? Or is that our description cannot be complete while the reservoir itself is deterministic in the underlying course of nature?

Reservoirs are not random, but are causal in nature, yet indeterministic because of our inability to formulate a complete and precise description and characterization. In other words, although a reservoir was geologically deposited, and thus causal, it cannot be deterministically defined or completely determined because of subsurface complexity and limited data. However, despite the fact that a reservoir or, more generally, a geologic phenomenon is not random, it is legitimate to model it using a stochastic function (commonly with a "random" component) because of the indeterminacy aspect. In fact, probabilistic approaches provide methods of choice for modeling subsurface heterogeneities, including geologic facies (Ma, 2009b) and petrophysical properties (Journel and Alabert, 1990). Furthermore, regardless of the methodology used, uncertainties will always exist in reservoir characterization, and probabilistic methods provide viable tools for uncertainty analysis and quantification (Deutsch and Journel, 1992).

Although the uncertainty principle may have been somewhat accepted in reservoir characterization, its practicality has been rather limited. Some consider traditional frequency probability theory impractical because of infrequent data (Gillies, 2000; Ma, 2009b). Others think that the Bayes belief network cannot be fully believed because it is too subjective (Popper, 1959). Still others feel that spatial statistics, of which geostatistics is a major branch, is too specialized and too difficult to be popularized within the main geoscience community. In other words, three roadblocks limit the more extensive use of probability theory for reservoir uncertainty analysis: (1) unbelieved Bayes belief network (e.g., Popper, ‘I do not believe in belief’, 1979, p. 25, although this is not on geoscience application), (2) infrequent frequency probability, and (3) too specialized spatial statistics.

From a practical point of view, many examples of failed projects have occurred because of the failure to study subsurface heterogeneity and the lack of uncertainty analysis for reserve estimates and risk mitigation in the reservoir management and decision analysis. A successful drilling technology project sometimes becomes a great failure economically for these reasons.

The two goals of uncertainty analysis are to quantify the reservoir uncertainty and to reduce it. This is critical because optimal reservoir management, including production forecasting and optimal depletion, requires knowledge of the reservoir characterization uncertainties for business decision analysis. Three questions need to be answered in reservoir uncertainty analysis.

- "How much do we know?" This means that we need to gather as much knowledge as possible about the reservoir, and analyze and interpret all available data.
- "How much can we know?" Not only should we gather as much data as we can, but we should also thoroughly explore the data to extract the maximum information. Thus, we would conduct exploratory data analysis using geologic, geophysical, and petrophysical principles, as well as geostatistical methods. Moreover, we ought to weigh the potential benefits of acquiring additional data to gain sufficient information and knowledge to make critical business decisions. In other words, we must weigh the value of information (VOI) versus the cost of information (COI).
- "How much should we try to know?" Like the EPR paradox in quantum mechanics, subsurface complexity and limited data prevent us from achieving a total understanding of a reservoir or completely describe every detail of subsurface heterogeneities. Therefore, our main emphasis in reservoir characterization should be to define relevant objectives that impact the business decision and to find realistic solutions accordingly. In other words, we must define what we really need to know or how much we should try to know to make the necessary business decisions.

**PREDICTION, MODELING, AND UNCERTAINTY ANALYSIS**

**Prediction and Modeling**

Many have aptly expressed the importance of prediction in science. Take, for example, Poincaré’s well-known saying, “It is far better to foresee even without certainty than not to foresee at all” (Poincaré, 1913,
In reservoir characterization, prediction is not only necessary, but also ubiquitous. Because of subsurface complexity and limited data, however, our predictions of reservoir properties inevitably involve uncertainties.

Geologic and reservoir models are commonly built to help field development planning or simply to enhance our geologic understanding of a reservoir. Modeling is a form of prediction using one or more quantitative methods, that involve uncertainty. It is highly challenging to analytically define three-dimensional (3-D) reservoir properties because complex subsurface heterogeneities occur at many different scales. We can model them, however, using geologic and petrophysical principles and probabilistic methods. For a model to represent reality as accurately as possible, the modeling method should integrate all the available data in a coherent way. Because no unique solution can be found with the lack of data, a good modeling method should enable uncertainty analysis and quantification.

In reservoir characterization, geostatistical methods have been used for both modeling and uncertainty analysis (Deutsch and Journel, 1992; Ma et al., 2008). Advantages of geostatistical methods, as compared with traditional mapping techniques, include the capabilities of better modeling subsurface heterogeneities and uncertainty analysis of geologic and petrophysical variables, which will be further discussed in a following section, Inference Uncertainty.

Uncertainty Analysis and Modeling

To analyze uncertainty in reservoir characterization and modeling, it is convenient to put it under the framework of a scientific process. That is, uncertainty in the reservoir characterization and modeling is caused by the uncertainty in the input data and uncertainty in the inference, as shown in Figure 1. Uncertainty analysis, therefore, should include studies of data inaccuracies and inference uncertainty from data to estimation of reservoir properties. These will allow a more accurate quantification of the uncertainty in the modeling result, which then can be used for reservoir management decision analyses.

An integrated reservoir modeling workflow typically includes data analysis, interpretations, selection of an appropriate method that integrates the available data from various disciplines, and definitions of the modeling parameters. All these tasks involve uncertainties. In other words, uncertainty can be an inaccuracy in data or indeterminacy in reservoir parameters.

Measurement Uncertainty

Uncertainty in data is mainly caused by uncertainties in measurements and secondarily by data handling. Several organizations, including the International Standardization Organization (ISO), the Bureau International des Poids et Mesures (BIPM, 2008; 2009), and the National Institute of Standardization and Technology (Taylor and Kuyatt, 1994), have proposed guidelines for reporting measurement uncertainties. Traditionally, the most common approach was to offer the best estimate that includes the expression of systematic and random errors in measurements. More recently, ISO and BIPM have changed their guidelines to recommend an approach involving the best estimate with associated uncertainties. The rationale they offered for this approach was that “no measurement is exact” and “it is not possible to state how well the essentially unique true value of the measurand is known, but only how well it is believed to be known” (BIPM, 2009, p. 2–3).

Uncertainty should be defined so as to characterize the dispersion of a measurement. Probability distributions are typically used to characterize such measurement uncertainties. The most commonly used probability function for stochastic uncertainty characterization is the Gaussian density, in which variance or standard deviation characterizes the dispersion of the measurement values. However, a nonaleatoric uncertainty commonly, but not always, requires a non-Gaussian density function.

Inference Uncertainty

Inference uncertainty is much more complex than measurement uncertainty and is more difficult to deal with. In reservoir characterization, inference uncertainties include conceptual, interpretational, and methodological uncertainties, to name a few. Because of the high expense of drilling, geoscientists commonly have to make assumptions and create conceptual depositional models, even with limited data in the early stage of
exploration. Therefore, conceptual depositional models typically contain significant uncertainties. In addition, geologic and seismic interpretations are commonly limited by the quantity and quality of data and are prone to cognitive biases, especially a confirmation bias (Ma, 2010). As such, interpreted results also contain significant uncertainties. Examples of uncertainty analysis in well-log and petrophysical interpretations can be found in the chapter by Moore et al. (2011).

The conceptual and interpretational uncertainties previously discussed can propagate into reservoir modeling. Moreover, geologic, petrophysical, and statistical parameters used in modeling have uncertainties. For example, few data are available in early field development, and uncertainty is typically high in the net-to-gross (NTG) ratio (Journel and Bitanov, 2004). Similarly, uncertainties in facies proportion and other geologic and petrophysical parameters can be quite significant (Haas and Formery, 2002; Friedmann et al., 2003). Furthermore, choice of the modeling method (e.g., between probabilistic and analytical approaches or between different probabilistic methods) can be ambiguous (Falivene et al., 2006), and specifications of petrophysical parameters in reservoir modeling and uncertainty analysis are commonly ambiguous as well.

Geostatistics has been used to model geoscience phenomena in the last half century (Journel and Huijbregts, 1978; Chiles and Delfiner, 1999; Hu and Le Ravalec-Dupin, 2004). Geostatistical techniques enable integrations of various data types and modeling of subsurface heterogeneities in depositional facies (Ma et al., 2009) and petrophysical properties (Goovaerts, 2006); however, both kriging and stochastic simulation have significant limitations in assessing local uncertainties. For example, multiple realizations in a traditional stochastic simulation are equally probable, and their inferential differences lie only in the random seeds (although new information can change this, which is discussed below). It is generally difficult to quantify spatial uncertainties of a reservoir model using geostatistics alone. The selection of a model among many realizations for dynamic simulations can be highly challenging as well. Several methods, including gradual deformation, optimization (such as probabilistic perturbation and simulated annealing), and the Kalman filter (Deutsch and Journel, 1992; Hu et al., 2001; Caers, 2007; Zafari and Reynolds, 2007), have been proposed to help select or postprocess geostatistical reservoir models, with various degrees of success.

It is, nonetheless, more straightforward to assess uncertainties of some “composite” reservoir variables, such as pore and hydrocarbon volumetrics, using stochastic simulations. In fact, applications to volumetric assessments have been quite extensively discussed (Berteig et al., 1988; Ma et al., 2008), and more examples can be found in several chapters in this volume.

Uncertainty analysis in reservoir characterization also includes transfer of the geologic uncertainty in a reservoir model to reservoir performance forecasting (Ballin et al., 1993; Vanegas et al., 2011), a stochastic history match that deals with both geologic and engineering uncertainties (Amudo et al., 2008), and uncertainty reduction and quantification using model updating with production data assimilation (e.g., Devegowda and Gao, 2011). To date, several methods have been proposed to deal with dynamic uncertainties or transfer of the static uncertainty to dynamic uncertainty, including experimental design (Friedmann et al., 2003), gradual deformation (Hu and Le Ravalec-Dupin, 2004), proxy models (Vanegas et al., 2008), Kalman filters (Zafari and Reynolds, 2007), and distance-based approaches (e.g., Caers and Scheidt, 2011).

**Parameter Uncertainty Quantification**

Similar to the uncertainties in measurements, uncertainties of reservoir parameters are typically characterized by a probability distribution. Uncertainty quantifications of these parameters in early field development based on various data sources and geologic scenarios have been discussed by many (Haas and Formery, 2002; Journel and Bitanov, 2004; Caumon et al., 2004). Parameter uncertainty in experimental design is commonly categorized into two or three levels, such as low, medium, and high, instead of using a probability distribution.

**Remarks**

Uncertainties in data and inference (e.g., reservoir modeling) naturally lead to uncertainties in the results of reservoir characterization. As previously mentioned, some “composite” reservoir parameters, such as hydrocarbon pore volume, are expressed by several other geologic and petrophysical variables, and their global uncertainties can be quantified by a probability distribution constructed by building multiple scenario models and multiple realizations of each contributing property.

Probability distributions of uncertain quantities in reservoir characterization are generally empirical, although some general mathematical laws may cause them to be nearly normal or lognormal. Addition of multiple random variables tends to produce a normal distribution as a consequence of the central-limit theorem (Papoulis, 1965, p. 266), and multiplication of many variables tends to yield a lognormal distribution (Aitchison and Brown, 1957). The resultant probabilistic distribution, however, will be highly influenced
by the distributions of the input variables and their correlations, especially when data are limited. For example, the histogram of the oil-pore volume is highly influenced by the histograms of porosity and oil saturation ($S_o$), as shown in Figure 2.

THE VALUE OF INFORMATION

Because uncertainty can be considered as an under-determination problem, more data could naturally reduce the uncertainty. This is the “value of information.” The VOI is discussed mostly under the framework of decision analysis in the oil and gas industry (Cunningham and Begg, 2008; Bratvold et al., 2009; Bailey et al., 2011). The focus here is on the VOI in reducing uncertainties in reservoir characterization and management. The VOI is most obvious in a totally random system, such as a lottery. The Powerball analogy (Ma and Gomez, 2009) can be used to illustrate the VOI. Powerball currently has two drums of numbers: the first is composed of 59 numbers and the second is composed of 39. Five numbers are drawn from the first drum, and one (the Powerball) is drawn from the second. The probability of winning the grand prize for each ticket (a combination of six numbers) is approximately one in 195 million (Powerball, 2010), such as

$$\frac{(59 - 5)! \times 5!}{59!} \times \frac{1}{39} = \frac{1}{195,249,054}$$

Assuming one could play after the first two drawings, the winning probability would increase to one in slightly more than one million, such as

$$\frac{(57 - 3)! \times 3!}{57!} \times \frac{1}{39} = \frac{1}{1,141,140}$$

In other words, knowing two numbers would yield a 17,100% increase in the winning odds (i.e., 195.25/1.14 ≈ 171). The VOI in reducing the uncertainty in this case is self-evident.

Similarly, using more data could significantly reduce uncertainty in reservoir characterization. An example of VOI by comparing depositional facies classifications using two well logs versus one well log is found in chapter 6 in this volume. Pitfalls exist, however, because a reservoir is not random or data quality may be questionable. More data sometimes cause more “apparent uncertainties.” This complication can be caused by subsurface heterogeneity or data heterogeneity or quality. Before examining examples of inference bias related to subsurface heterogeneities, various types of data in reservoir characterization are briefly reviewed.

Because reservoir characterization is a multidisciplinary process, it involves different types of data, including hard data and soft data. Typically, hard data provide direct information, whereas soft data are considered to be indirect information. For example, core data commonly provide direct measurements of rock formations, whereas seismic data commonly provide indirect information of rock formations. Some well logs may be used as direct information, whereas others are rather indirect information (Moore et al., 2011). Although interpretations are not primary data, sometimes they can be used as soft data. For example, an early task in the reservoir characterization is geologic interpretation, the results of which are commonly used for reservoir modeling.

Hard Data and the Value of Information

In petroleum geostatistics, hard data are commonly synonymous with reliable information. A simple synthetic example shown in Figure 3 demonstrates the VOI using NTG ratios. Assume that only three hard data points at the well locations in Figure 3A are initially available. It would be difficult to know if the area contains significant hydrocarbon resources because considerable uncertainty exists regarding the global NTG and depositional model. By adding four wells, which show high NTG ratios (Figure 3B), it would be reasonable to delineate a channel complex in the area, assuming...
that the delineation is consistent with the regional geology. Thus, the four additional data points would provide valuable information that improves our understanding of the prospect.

**Soft Data and the Value of Information**

Typically, reservoir characterizations lack sufficient direct measurements. Thus, reservoir models built only with hard data tend to be too unconstrained and lacking in geologic realism (Massonnat, 1999). However, geologic conceptual models tend to capture regional characteristics but inadequately represent smaller scale subsurface heterogeneities. An integrated approach that combines both geologic knowledge and hard data can help more accurately model the reservoir and reduce the uncertainty.

Many geostatistical methods enable integration of soft data, provided that geologic knowledge is numerically represented in trend maps or trend curves. In addition, a methodology based on the hierarchy of subsurface heterogeneities can improve the integration of a variety of geologic information, including use of stratigraphic reference classes and spatial propensity analysis (Ma et al., 2009). For example, facies data can be integrated with a depositional conceptual model to create facies probabilities, which then can be used to constrain a geostatistical model to be geologically more realistic (Ma, 2009b; Yu et al., 2011).

**Value of Information and Sampling Bias**

In theory, as more data become available, our knowledge of the reservoir should improve. A sampling bias, however, can complicate the VOI. Consider the example illustrated in Figure 3. The average NTG based on the first three wells was 23%. After drilling the four additional wells, the average NTG from all the seven wells was apparently 57%. However, the delineated channel complex, which represents about three-fifths (60%) of the area, had five data points. The overbank area, which represents two-fifths (40%) of the area, had only two data points. Thus, a sampling bias exists, which should be accounted for. The global NTG estimated using the polygonal tessellation or propensity zoning–based declustering (Ma, 2009b) is about 48%. The 57% global NTG from the average of the raw data represents nearly a 19% overestimation (i.e., \([0.57 - 0.48]/0.48 \approx 19\%\)).

Sampling bias is generally unavoidable in exploration and production. Commonly, simply for economic reasons, it is intentional. No one wants to spend tens of millions of dollars to drill a dry hole just for collecting data. Operators drill wells in what is thought to be the best parts of the reservoir or play, and data obtained from these wells may not represent either average or the full range of reservoir properties. Whereas avoiding sampling bias is difficult in general, the main task should be learning how to incorporate it in business and reservoir modeling decision making. Aiming to drill in the “sweet spots” in light of subsurface heterogeneities makes predictions from data to a reservoir model particularly treacherous. In some cases, declustering can be performed to mitigate sampling bias. In other cases, inference needs to be made that accounts for the sampling bias (Ma, 2009a).

**Value of Information versus Cost of Information**

The VOI lies in reducing uncertainty when more information is used. From a perspective of reservoir management, we must also consider the COI. The difference between the VOI and COI is known as the “net value of information” (NVOI). In reservoir characterization and management, the following questions that weigh VOI and COI commonly arise:

- Should we acquire a new 3-D seismic survey?
- Should we drill a few new wells to delineate the reservoir?
- Should we core this well?

To answer these questions, we need to estimate the VOI versus the COI. Generally, if the VOI outweighs
the COI, that is, a positive NVOI, it is worth obtaining new information. In short, more data will help more accurate reservoir characterization; but for reservoir management, the benefit of collecting more data (i.e., VOI) might be weighed against the cost of collecting data. Obtaining the necessary data at the minimum cost is one important principle for reservoir management (Thakur, 1990).

**Cost of Misinformation**

An important element of the VOI is the quality of information or data quality. If data quality is very poor, it does not provide useful information. In fact, it may lead to erroneous results. This is the “cost of misinformation” (COM). The COM includes both the COI and the damage caused by the misinformation. Damage from the COM could be much greater than the COI. In the example shown in Figure 3B, imagine that the actual NTG datum in the central area was 10% instead of 100%. In that case, the depositional model and the global NTG ratio would be wrong. This likely would lead to a misunderstanding of the reservoir and a poor decision for reservoir management.

Clearly, the COM includes the cost of errors simply because errors represent misinformation. Jablonowski et al. (2008) discussed how to assess the cost of errors in reserve estimates and other production and economic variables.

**VARIABILITY, UNCERTAINTY, RISK, AND DECISION ANALYSIS**

Although the definitions of variability, uncertainty, and risk are provided in the glossary of this volume, it is useful to discuss them here in more detail. In particular, exploring the relationships among these concepts can illuminate our understanding of their differences and applicabilities in reservoir characterization and reservoir management.

**Variability and Uncertainty**

In reservoir characterization, “variability” refers to the magnitude of change of a geologic process, petrophysical property, or any reservoir variable. Variability is totally objective as it is simply a property of a phenomenon. Generally, subsurface variability is high because multiple scales of heterogeneities exist, such as in structure, stratigraphy, depositional facies, petrophysical properties, and fluids. As such, characterization of subsurface variability is rather complex. Geostatistical methods are commonly used to model the spatial variability of facies and petrophysical variables (Deutsch and Journel, 1992; Ma, 2009b; Ma et al., 2011). Note that early geostatistical approaches mostly used kriging methods because of their local estimation accuracy. Conditional stochastic simulation was proposed (Journel and Huijbregts, 1978; Dubrule, 1989) to better model the spatial variability of geoscience phenomena. Although various kriging methods are still largely used in the mining application, stochastic simulation has been more commonly used in petroleum geostatistics, especially to describe and characterize the connectivity of rock properties (Journel and Alabert, 1990).

Uncertainty, however, is simply the result of our not knowing enough about a variable. Uncertainty may refer to inaccuracy in data or indeterminacy or indefiniteness of a variable. Uncertainty differs from variability in that even when a parameter has no variability (i.e., a constant), uncertainty may still exist simply because we have no information about it. However, uncertainty is commonly highly correlated with variability because high variability tends to cause more unknowns, consequently more uncertainties. An example of future oil price, which is discussed below, will further illustrate this relationship.

**Error and Uncertainty**

It is important to distinguish uncertainty from error. Whereas an error is the difference between an individual result and the true value of a quantity, uncertainty of a quantity takes the form of a range as a result of the unknown factors. Nevertheless, an intrinsic relationship exists between error and uncertainty (Ma, 2010). Larger uncertainties in the input data are more likely to cause errors in the reservoir characterization result and business decision. Conversely, errors in geologic, geophysical, petrophysical, or engineering data will cause more uncertainties in reservoir characterization and modeling.

**Uncertainty and Risk**

In common language, “risk” may simply refer to the possibilities that undesirable events may occur. For example, a risk exists that a well might be a dry hole, or, smoking increases the chance of lung cancer. In this sense, risk and uncertainty have somewhat similar connotations. More theoretically, however, “risk” is defined as the product of the probability of occurrence of an undesirable event and the consequence of its occurrence (see Glossary). Therefore, risk has two components: an uncertainty component and a consequence component. Note that although sometimes
risk apparently refers to variability (Markowitz, 1991, p. 188) or uncertainty, it may still implicitly connote an unspecified consequence of the uncertainty.

Because of the consequence component of the risk equation, risk has a direct impact on decision analysis. For example, a possible perdition (or any loss) caused by a bad prediction is part of risk analysis but not part of uncertainty analysis per se. In fact, it is commonly argued that the consequence of being wrong must dominate the probability of being wrong in decision analysis. As previously mentioned, the Port-Royal authors’ historic argument that fear of harm should be proportional to the probability of an event (Arnauld and Nicole, 1662) supports the notion of uncertainty analysis, but it says nothing about the consequence component of the risk. As Bernstein (1998, p. 100) noted regarding the Port-Royal philosophy, “only the pathologically risk-averse make choices based on the consequences without regard to the probability involved.” By contrast, modern risk analysis, which was developed under the framework of utility theory, argues that “only the foolhardy makes choices based on the probability of an outcome without regard to its consequences” (Bernstein, 1998, p. 100).

**Risk and Reward**

Risk should be discussed with reward because risk could be reduced to zero if one does not care about the potential benefit. It is well known that the oil exploration and production business is highly risky, but potential rewards should not be ignored. Otherwise, no one would take the risk to find oil. Pratt (1952) gave good examples of risk taking in the early days of the oil business. He described that many early explorers in the United States took high risks to drill wells at “unfavorable” locations and discovered major oil fields. He summarized this phenomenon by saying (p. 2235) “Since the very inception of the industry, the finding and producing of oil in the United States have been carried on by literally thousands of independent enter-

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**Table 1. Illustration of the EMV method for evaluating two alternative choices.**

<table>
<thead>
<tr>
<th>Possible Outcome</th>
<th>Probability</th>
<th>Net Present Value</th>
<th>Expected Value</th>
<th>Drill EMV</th>
<th>Farm Out EMV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry hole</td>
<td>0.30</td>
<td>−$1,000,000</td>
<td>−$300,000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 million bbl</td>
<td>0.35</td>
<td>$2,000,000</td>
<td>$700,000</td>
<td></td>
<td>$2,000,000</td>
</tr>
<tr>
<td>10 million bbl</td>
<td>0.25</td>
<td>$4,800,000</td>
<td>$1,200,000</td>
<td></td>
<td>$2,400,000</td>
</tr>
<tr>
<td>25 million bbl</td>
<td>0.10</td>
<td>$18,000,000</td>
<td>$1,800,000</td>
<td></td>
<td>$6,000,000</td>
</tr>
<tr>
<td>Expected monetary value (EMV)</td>
<td></td>
<td>$3,400,000</td>
<td>$1,900,000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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This phenomenon explains why the United States produced nearly two-thirds of all the oil that the world had consumed before 1952, and the discovered hydrocarbon resource between 1920 and 1952 was nearly nine times greater than the previous estimate of the total resource! By these historical examples, we don’t mean to imply that taking risks will always allow one to reap the reward. By definition, risk implies possibility of a negative consequence.

Traditionally, evaluation of a project or proposal was mostly based on cost-benefit analysis (CBA). This allows decision makers to assess the monetary value of a proposal or project, in which all the costs and benefits at different times are converted into net present values (NPVs) with assumed rates of return on investments. When uncertainty is present, CBA should be evaluated with respect to the probability of occurrence for each possible outcome. Evaluating expected monetary value (EMV) (Ikoku, 1985; Bell, 2007), or expected return (Markowitz, 1991), is a basic method of calculating the potential benefit under uncertainties. This method includes the following steps: (1) defining possible outcomes, (2) assigning the probability for each possible outcome, (3) evaluating profit or loss (e.g., in terms of NPV) for each outcome, (4) computing the weighted average profit or loss (i.e., expected value [EV]), and (5) selecting the scenario that has the highest EMV or expected return.

Table 1 gives a simple example of two alternatives (drill or farm out) with four possible outcomes. The drilling EMV ($3.4 million) is greater than the farm-out EMV ($1.9 million) and, therefore, is a better alternative.

The EMV method considers not only the probabilities of different scenarios, but also their corresponding monetary costs and profits. As such, better decisions can be made using this method compared with methods purely based on probabilities (Taleb, 2005, p. 98–101). Nevertheless, the EMV method has several
pitfalls, including difficulties involved in choosing possible outcomes and in accurately assigning corresponding probabilities of occurrences. In many cases, these parameters cannot be adequately defined. Another more important shortcoming of the EMV lies in no consideration of the consequence of the risk. In fact, the sole objective of maximizing expected monetary return has been found inadequate since the 1800s because many risk-taking strategies based on probability could not be explained, notably the St. Petersburg paradox (Savage, 1972, p. 93; Bernstein, 1998, p. 106–108). An investment may be good for a particular investor or company, but it may not be good for another investor or company because of their different financial and organizational situations. Hence, the consequences differ. Some may prefer more conservative investments with lower but surer returns, whereas others may prefer more aggressive investments with potentially higher returns.

The utility theory is capable of considering the different preferences of investors and companies (Ikoku, 1985; Markowitz, 1991; Bell, 2007). Although a detailed discussion on utility theory is beyond the scope of this chapter, Figure 4 illustrates two simple utility functions. The straight dotted line represents impartiality toward profit or loss. Impartiality here does not imply stoicism. Instead, it means that the magnitude of the pain caused by the loss of money is the same as the magnitude of pleasure caused by the gain of an equivalent amount of money. In many real cases, the sadness (negative utility) caused by a loss affects people more significantly than happiness (positive utility) that a gain creates. The solid curve in Figure 4 represents such a risk-averse preference. Notice the gradual increase in utility for gains and the steeper drop in utility for losses. In this risk profile, an investor (or a company) must gain about $3.5 million (utility = 5) to achieve a magnitude of happiness equal to the pain of a loss of just $0.5 million (utility = −5). Kahneman and Tversky (1979) derived a risk preference curve (also called value function) that is concave for gain and convex for loss with steeper drops. Many consider this value function representative of most people’s risk profile. More risk profiles can be found in Ikoku (1985, p. 203–209) and Markowitz (1991, p. 286–294).

The common saying “Am I paid for the risk I’m taking?” nicely characterizes the principle of balancing the risk and reward. Consider the following method of achieving such a balance. Figure 5 illustrates the well-known risk-reward relationship from the modern portfolio theory (Markowitz, 1952, 1991), which helped Markowitz win the 1990 Nobel Prize in economics. In general, a certain relationship, albeit a cloud relationship (i.e., large spread in the crossplot), exists between the risk taken and the potential profit from the investments. Whereas risk-averse investors should choose low-risk investments, risk takers may want to choose higher risk investments for potentially greater returns. Because of the loose cloud relationship between the risk and reward, regardless of the risk profile, it is wise to choose investments close to the “efficient frontier,” which represents the highest return for a given risk taken. An even better choice would be to maximize the potential reward while minimizing the risk. This principle can be applied to reservoir optimization (Bailey et al., 2011) and exploration and production project selection and management (Adams et al., 2001). Note that “risk” in this context refers to the undesired variability.
When the consequence component is also considered, the risk is nicely described by the common saying, “Is the probability that I end up with a ‘goose egg’ too high for me to handle the consequence?”

Decision Analysis Under Uncertainty or Risk

Pascal’s famous “wager” in his book, *Penseés* (Pascal, 1670; Hajek, 2008), may have been one of the earliest and most widely known contributions to decision analysis under uncertainty (Miles, 2007). Modern decision analysis, however, has developed mostly since the end of World War II, incorporating utility theory and risk preferences into making decisions under uncertainty and risk. In general, it is wise to reduce uncertainty to a reasonable level before making a decision, advice aptly captured in the saying, “Nothing can be concluded until the uncertainty is mitigated.” As previously noted, the VOI is one way of mitigating uncertainties. Improving the technologies, methods, and processes of reservoir characterization can also mitigate uncertainties for reservoir management. Even after mitigating uncertainty, however, we must still make decisions under uncertainty, albeit less than before. Therefore, our ability to make decisions under uncertainty is critical both in business and in life. Here, the risk equation, and more specifically, the consequence component of the risk equation, is a factor. Figure 5 shows that as risk increases in a project or investment, uncertainty in the return increases, whereas the probability of a higher return improves. The question is: Can we afford the loss? If not, then reducing the risk will be in order, although this will also reduce potential returns on the investment.

Table 2 illustrates a simple example of a decision analysis under uncertainty and risk in which two choices exist. The drilling EMV ($2,500,000–$500,000 = $2.0 million) is greater than the farm-out EMV ($1.25 million). Therefore, based on the EMV, which considers the uncertainties of these two outcomes, we should drill. However, if we are very risk averse, having the risk preference of the solid curve in Figure 4, we could calculate the utilities of the drilling and farm out as follows:

\[
\text{Utility of drilling} = 0.5 (-5) + 0.5 (4) = -0.25
\]

\[
\text{Utility of farm out} = 0.5 (0) + 0.5 (2) = 1.00
\]

Because the utility of farming out is greater than that of drilling, we should farm out the property. This example shows how EMV enables us to make decisions under uncertainty, whereas the utility theory enables us to make decisions under risk, provided that the risk profile is defined. Obviously, a simple utility function was used in this example. In practice, the definition of the utility function based on the company’s particular situations may be quite challenging, and utility also changes with time (Grayson, 1962).

Other methods of decision analysis under uncertainty have been proposed. For example, material uncertainties (e.g., rig or seismic equipment uncertainty) can be integrated into a business decision through an appropriate valuation of future information using decision trees or Monte Carlo simulation (Prange et al., 2006; Bailey et al., 2011). For cases of extremely high risk, we may need to make special considerations in decision analysis (Taleb, 2007).

Example: Oil Price Variability, Uncertainty, and Risk

Crude oil price (COP) is volatile and its impact on the exploration and production business is extraordinarily large. Figure 6 shows the weekly COP from January 1997 to August 2009. Overall, the COP shows a very high variability, but it varies more in some periods than others, notably during the last 2 to 3 yr. Between August 2006 and August 2009, the COP average was $73.08, with a standard deviation of 24.84. By contrast, the COP average from January 1997 to December 1999 was $15.75, with a standard deviation of 4.21. Obviously, COP variability during the last 3 yr has been much greater. As previously mentioned, because variability is simply a property of a phenomenon, it is totally

<table>
<thead>
<tr>
<th>Possible Outcome</th>
<th>Probability</th>
<th>Net Present Value</th>
<th>Expected Monetary Value</th>
<th>Net Present Value</th>
<th>Expected Monetary Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry hole</td>
<td>0.50</td>
<td>−$1,000,000</td>
<td>−$500,000</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10 million bbl</td>
<td>0.50</td>
<td>$5,000,000</td>
<td>$2,500,000</td>
<td>$2,500,000</td>
<td>$1,250,000</td>
</tr>
</tbody>
</table>

Table 2. Illustration of the utility method for evaluating two alternative choices.
objective. However, uncertainty is a result of unknowns. No uncertainty is seen in the COP shown in Figure 6 simply because it is a collection of historic data. Nonetheless, the high variability of COP over time would imply a high degree of unpredictability or high uncertainty in the future COP.

Figure 7A shows a plot of monthly COP data from January 2000 to September 2002 and the predicted COP for October 2002 to December 2003 by the U.S. Energy Information Administration (EIA). Because of the relatively low variability in the COP between January 2000 and September 2002, the uncertainty range of the prediction was quite small. Figure 7B shows the actual weekly COP data. It fell within the EIA (U.S. EIA, 2009) predicted uncertainty range, which had a 95% confidence interval. Nevertheless, variability in the actual COP was greater than in the prediction.

It is possible for the COP to go outside of the 95% confidence uncertainty range. In the fall of 2007, for example, no one predicted that the COP would reach $140 per barrel in 2008. When it actually reached that price in the summer of 2008, no one predicted it would drop below $40 per barrel by the end of 2008. Some even suggested that the $50 COP was history, and that it would never happen again. Needless to say, it did. The high variability in the COP during the last 2 to 3 yr caused the EIA and other institutions to increase the uncertainty range of their COP predictions. Figure 8 shows the EIA (U.S. EIA, 2009) prediction of the yearly average COP from 2009 to 2030. The large uncertainty range in the prediction reflects mainly the impact of the high COP volatility during the last 3 yr. Note also that the range increases as a function of time, reflecting greater uncertainty as the prediction moves away from the existing COP data.

Although uncertainty in the COP may be essentially the same for all the exploration and production companies, each company’s risk relative to it may be very different because the consequences of dramatic changes in the COP vary from one company to another. A dramatic plunge in the COP during a short period, as we witnessed during late 2008 to early 2009, caused severe budget constraints in some companies. Others experienced less impact because of their asset base, diversification, and/or hedging.

CONCLUDING REMARKS

Although a reservoir is the result of geologic processes and is not random (when we say that it is random, we say it heuristically), it is legitimate to use probabilistic approaches in reservoir characterization and modeling. Probabilistic methods should be used in combination with established geologic, petrophysical, geophysical, and reservoir engineering principles in reservoir characterization.

Generally, many types of uncertainties exist in reservoir characterization. Data uncertainties, if not mitigated, can propagate into subsequent reservoir characterization processes and cause greater uncertainties or errors in the results. Improving measurement tools can mitigate measurement uncertainties. Inferential uncertainties can be mitigated by acquiring more data, and/or using better science and technology.
Figure 7. (A) Monthly crude oil price (COP) projection by the U.S. EIA (2009) for the period from October 2002 to December 2003. Data from January 2000 is shown for reference. The band between the two dotted lines represents the uncertainty range with 95% confidence. (B) Actual weekly COP during the same time span (from U.S. EIA, 2009).

Figure 8. Yearly average crude oil price (COP) from 1980 to early 2009 (historic data) and projections (solid curve) to 2030 with an uncertainty range (band between the two dashed curves) (from U.S. EIA, 2009). Note that the yearly average COP has less variability than monthly, weekly, or daily averages. For example, the average COP in 2008 was about $100, whereas the weekly average COP ranged from $36 (in the week of December 26) to $137 (in the week of July 4).
One of the main reasons to analyze and quantify uncertainty is to enhance decision analysis. In general, business decisions are made under uncertainty because uncertainty may be mitigated, but cannot be completely eliminated. How much we attempt to mitigate uncertainty should depend on the needs of decision analysis and the cost of information. Uncertainty analysis should not be for its own sake, but instead should support investigational analyses, decision analysis under uncertainty and risk management. With limited data, it is impossible to describe subsurface heterogeneities at all levels of detail. But it is possible to describe them in relevant details. To know what needs to be known and to know what can be known (e.g., by balancing the complexity of the problem, availability of information, cost of acquiring new information, and timeline, etc.) should be the main focus of uncertainty analysis in reservoir characterization and management.

ACKNOWLEDGMENTS

The author thanks Schlumberger Ltd. for permission to publish this work and the reviewers for the useful suggestions.

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