From Uncertainty Quantification to Decision Making in the Oil and Gas Industry[1]

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In this paper, we present the findings of a large (N = 494) survey of oil and gas professionals that addressed the following two questions: Has uncertainty quantification improved in the oil and gas industry over the last five years? Has this improvement translated into improved decision making? Our results suggest that the answer to the first question in an unequivocal "yes," but that the answer to the second is qualified "no." How could this be?
Uncertainty quantification is not an end unto itself; removing or even reducing uncertainty is not the goal. Rather, the objective is to make a good decision, which in many cases requires the assessment of the relevant uncertainties. The oil and gas industry seems to have lost sight of this goal in its good-faith effort to provide decision makers with a richer understanding of the possible outcomes flowing from major decisions. The industry implicitly believes that making good decisions merely requires more information.
To counter this, we present a decision-focused uncertainty quantification framework, which we hope, in combination with our survey results, will aid in the innovation of better decision-making tools and methodologies.

Key words: decision analysis, uncertainty, risk, oil and gas
History: Submitted to the Energy Exploration and Exploitation on 29 October 2008. Revised and resubmitted 15 December 2008.

1. INTRODUCTION

The use of probabilistic modeling in the oil and gas industry has increased significantly over the last 10 years, as evidenced by the large number of publications and Society of Petroleum Engineers (SPE) workshops and forums dedicated to the topic. For example, Table 1 lists every SPE forum since 1979 that has dealt with uncertainty, prediction, or decision making. This information is interesting in two respects. First, six out of the eight forums have taken place in the last 10 years. Second, only one forum includes the word "decision" in the title, suggesting a strong focus by the petroleum engineering community on uncertainty quantification rather than decision making.

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[1] This paper was originally presented as SPE 109610 at the 2007 SPE Annual Technical Conference and Exhibition, held 11-14 November 2007 in Anaheim, California.

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Table 1. Uncertainty- or Decision-focused SPE Forums (1979–2007)

Year	Venue	Title
1991	Europe	Managing Uncertainties in Field Development Planning and Reservoir Modeling
1995	North America	Risk and Confidence in Reserves Valuation
1997	Asia Pacific	Risk Assessment and Management of Uncertainty
2000	North America	Risk, Options, and Portfolio Management in the Oil and Gas Business
2001	Asia Pacific	The Application of Seismic Attribute Analysis and Geostatistics in Reservoir Prediction
2002	North America	Decision-Driven Asset Development & Management
2005	Europe	Risk Management and Integrated Business Modeling
2007	North America	The Future of Profit Prediction

SPE's Advanced Technology Workshops (ATW) series exhibits a similar trend, with recent meetings including "What do Geoscientists and Engineers Need to do to Better Manage Uncertainty?" (Dubrovnik, Croatia, 13–16 March 2006) and "Probabilistic Subsurface Assessments" (Houston, Texas, 18–20 July 2007 and 10-11 November 2008).

In light of this focus on uncertainty quantification and forecasting, it seems appropriate to scrutinize its perceived value. Has this focus on uncertainty quantification and forecasting improved decision making (by which we mean better quality decisions and not necessarily better outcomes)? Which uncertainties are viewed as being the most critical? Which new uncertainty-quantification methods should be developed? We set out to answer these questions through a large survey of oil and gas professionals.

The remainder of this paper is organized as follows. In the next section, we describe the survey design and implementation. In §3, we detail the survey results. In the §4, we address the survey findings by describing a decision-focused framework that we hope will guide the development of future uncertainty–quantification methods. In the final section, we suggest areas for improvement, which were uncovered by our survey and offer concluding remarks.

2. SURVEY DESIGN AND IMPLEMENTATION

The goal of the survey was to understand the use of probabilistic methods and decision-making methodologies in the oil and gas industry. Specifically, we hoped to understand the degree of improvement in uncertainty-quantification methods over the last five years and whether this had resulted in a similar increase in the quality of decision making.

To achieve this goal, we developed a set of 21 questions covering the following areas: demographic information, assessment of current decision process and uncertainty quantification methods, and recommendations for improvement.[2] We implemented the survey via the online service SurveyMonkey (www.surveymonkey.com), which allows

2 Please contact the authors for a copy of the survey questions.

users to enter their responses from any computer with Internet access. SurveyMonkey tracked the IP address of participants to prevent multiple responses, but the survey was otherwise anonymous. We targeted oil and gas professionals by emailing several SPE Technical Interest Groups and SPE local chapters around the world (please see the Acknowledgements for those groups that were kind enough to assist us). The survey was launched on 23 April 2007 and closed on 05 July 2007. A total of 494 people completed the survey over this time period.

3. SURVEY RESULTS

3.1 Demographics

We begin our discussion of the survey results with a summary of respondent demographics.

Employer: 62.4% of respondents worked for oil and gas companies (O&G), 16.6% were with service companies or software providers, 10.9% were consultants, 3.6% were academics, and 6.5% were self-employed, in government, or otherwise employed.

Company Size: 59.5% of respondents worked for "large" companies with more than 1000 employees, 14.6% worked for "mid-size" companies with 100 to 1000 employees, and 25.9% for "small" companies with fewer than 100 employees. Respondents that did not work directly for O&G companies (e.g., consultants) were asked to specify the size of the O&G companies with which they typically work.

Location: 43.7% of respondents were based in North America, 42.1% in Europe / Former Soviet States, 5.7% in Central/South America, 3.9% in Africa / Middle East, 1.4% in Asia, and 3.2% in other parts of the world. The large North American response is consistent with the demographics of the SPE membership. However, the survey results tend to slightly over represent the European and Former Soviet States and under represent Africa, the Middle East, and Asia. This outcome was driven by two factors: (1) the survey being in English and (2) the degree of support provided by the local chapters. While local SPE chapters from around the world were contacted, the response was not uniform (see Acknowledgements).

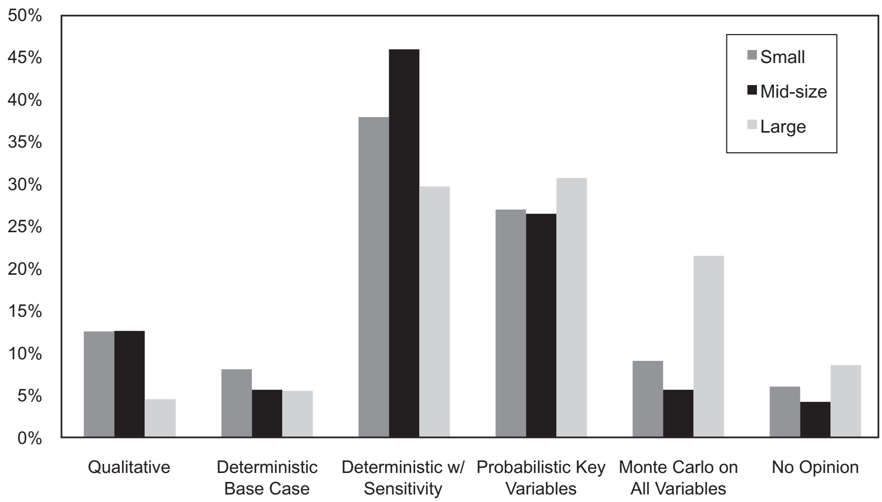
Job Title: 8.7% of respondents identified themselves as executives, 28.1% as managers/supervisors, 54.9% as professionals, 4.5% as educators, and 3.8% as other.

Asset Life Cycle: Respondents were able to specify where in the asset life cycle they primarily focused their efforts. Multiple responses were allowed. 47.2% were focused on exploration, 70.5% in development, 57.5% in production, and 7.3% were outside of these areas.

Job Function: Respondents were asked to identify themselves as decision makers (accountable for significant decisions or have expenditure authority) and/or as supporting decision making (providing recommendations to those who are accountable for significant decisions). Because individuals may play both roles at different levels, multiple responses were allowed. 29.2% identified themselves as decision makers and 80.6% as supporting decision-making processes. Decision makers were further asked the level, in USD, of decisions for which they were accountable. Since decision authority may span several budget levels, multiple responses were allowed. 52.7% indicated less than USD 1 million, 41.0% between USD 1 million and USD 10 million, 20.7% between USD 10 million and USD 100 million, and 12.3% over USD 100 million. Likewise, those who support decision makers were asked the level, in USD, of decisions they support. Again, multiple responses were allowed. 32.5% indicated less than USD 1 million, 40.1% between USD 1 million and USD 10 million, 42.0% between USD 10 million and USD 100 million, and 42.3% over USD 100 million.

3.2 Decision Process

Current Investment Analysis: Respondents were asked to describe the level of investment analysis used in the primary decision-making process of the organizations they work for (or with). Possible responses were qualitative, deterministic, deterministic with sensitivity analysis, probabilistic analysis on key uncertainties, or Monte Carlo analysis of all uncertainties. The results for small, mid-size, and large companies are given in **Fig. 1**. Small and mid-size companies rely primarily on qualitative or deterministic analysis, whereas large companies more extensively use probabilistic methods. In fact, over 20% of respondents working for large companies responded that the primary method of investment analysis is Monte Carlo simulation on all variables. Interestingly, mid-size companies rely the most heavily on deterministic analyses. There was not a significant difference in the use of probabilistic methods by geographic location.



Level	small	Mid-size	Large
Qualitative	12%	13%	4%
Determinist	8%	6%	5%
Determinist	38%	46%	30%
Probabilistic	27%	26%	31%
Monte Carlo	9%	6%	21%
No Opinion	6%	4%	9%

Fig. 1. Level of Investment Analysis Currently Used

Recommended Investment Analysis: Respondents were asked for the most detailed level of investment analysis they recommend for important decisions. The results appear in Table 2. 47% of respondents said they would never or rarely recommend qualitative investment analysis for important decisions. 31% felt that deterministic base case analysis was sometimes recommended. 50% usually or always recommend deterministic analysis with sensitivity analysis of key variables. The most often recommended level of investment analysis was probabilistic analysis of key variables, which was usually or always recommended by 55% of the respondents. Interestingly, neither Monte Carlo on all variables nor real options were recommended highly. In fact, real options are recommended almost as infrequently as qualitative analysis. That may be surprising given the great interest in real options only a few years ago.

Table 2. Recommended Level of Investment Analysis

	How Often Recommended			
Level of Investment Analysis	Never or Rarely	Sometimes	Usually or Always	No Opinion
Qualitative	47%	24%	18%	11%
Deterministic Base Case	29%	31%	29%	11%
Deterministic w/ Sensitivity	11%	29%	50%	10%
Probabilistic Key Variables	10%	25%	55%	10%
Monte Carlo on All Variables	26%	29%	32%	12%
Real Options	39%	25%	18%	18%

These results did not vary appreciably by company size or geographic region. Comparing Table 2 and Fig. 1, we see that while many large companies are using extensive Monte Carlo analyses, most respondents recommend probabilistic analysis focused on key uncertainties.

Current Decision Process: Respondents were asked to state their agreement with a series of statements regarding the quality of the decision-making process used by their organizations. The results appear in Table 3. Overall, respondents appear to be quite satisfied with the quality of the decision-making process used by their organizations. The two areas with the most room for improvement are, facilitating the comparison of investment opportunities and providing decision makers with the appropriate level of detail needed to make good decisions.

Table 3. Quality of Current Decision-making Process

Our decision making process…	Disagree	Neutral	Agree	No Opinion
Considers a range of investment alternatives.	6%	12%	78%	3%
Allows the evaluation of opportunities using a clear and consistent value measure (e.g., NPV).	5%	10%	82%	4%
Facilitates the comparison of investment opportunities.	6%	19%	70%	5%
Provides decision makers with the appropriate level of detail needed to make good decisions.	7%	19%	70%	5%
Creates value for our organization and is worth the effort.	5%	14%	77%	4%
Yields recommendations that are implemented sby management.	3%	16%	75%	6%

These results vary only slightly by decision level. For example, 67% of decision makers responded that their decision-making process facilitates comparisons among investments, compared to 70% overall. Another example, 75% of decision makers felt that they were given the appropriate level of detail needed to make good decisions, compared to 80% overall. Not surprisingly, perhaps, 80% of decision makers said that recommendations are implemented.

3.3 Uncertainty and its Quantification

Sources of Uncertainty: Respondents were asked to rate several sources of uncertainty for potential impact on the performance of investment decisions. The following scale was used: 1 = Minor Impact, 2 = Some Impact, 3 = Moderate Impact, 4 = Important Impact and 5 = Significant Impact. The overall ranked results are given in Table 4, along with the average score and the fraction of respondents that identified this uncertainty source as having either an important or a significant impact on investment results. We see that subsurface uncertainties are viewed as being a significant source of risk, closely followed by hydrocarbon prices. Furthermore, more than 50% of respondents felt that all but two of the categories (fiscal terms and geopolitical) were either important of significant sources of uncertainty.

Table 4. Ranking of Sources of Uncertainty

Uncertainty Source	Average Score	Important or Significant
Subsurface	4.4	82%
H. Carbon Prices	4.3	78%
Reserves	4.1	71%
Drilling	3.9	67%
Capital	3.9	66%
Schedule	3.6	57%
Production	3.5	53%
Facilities	3.5	52%
Operating Costs	3.5	51%
Fiscal Terms	3.4	46%
Geopolitical	3.2	43%

These results did not differ significantly by decision-making level.

Improving Uncertainty Quantification: Respondents were asked to rate the importance of improving uncertainty-quantification techniques in the areas listed in Table 4. The following scale was used: 1 = Counterproductive to Increase Detail, 2 = Improvements not Warranted, 3 = Minor Improvements Warranted, 4 = Improvements Warranted, and 5 = Significant Improvements Warranted. The overall ranked results are given in Table 5, along with the average score and the fraction of respondents that believe more than minor improvements are warranted.

Interestingly, while hydrocarbon prices are an important source of uncertainty (the second-highest-ranked uncertainty in Table 4), there is relatively little support for increasing the level of probabilistic modeling to capture this. This response probably stems from the belief that uncertainty in price tends to affect all projects to roughly the same degree. Furthermore, even the highest-ranking source in Table 5, subsurface uncertainty, received an average score of less than 4.0, with less than half of respondents recommending more than minor improvements. So, while some improvements are warranted in almost all areas, there is not significant support to further increase the complexity of probabilistic modeling. This result is somewhat surprising given the industry's history of failing to deliver on promised performance (Merrow, 2003) and that many executives are dissatisfied with their companies' performance, citing budget and cost overruns (McKenna et al., 2006). As we will see in §3.4, this response may stem from a realization that decision making is what counts and improving uncertainty quantification may not improve decision making.

Table 5. Importance of Improving Uncertainty Quantification Methods

Uncertainty Source	Average Score	More than Minor Improvements Warranted
Subsurface	3.5	47%
Reserves	3.5	45%
Schedule	3.4	41%
Drilling	3.4	41%
Capital	3.4	36%
Production	3.4	36%
Operating Costs	3.2	34%
Facilities	3.2	30%
H. Carbon Prices	3.1	29%
Geopolitical	2.9	24%
Fiscal Terms	2.8	20%

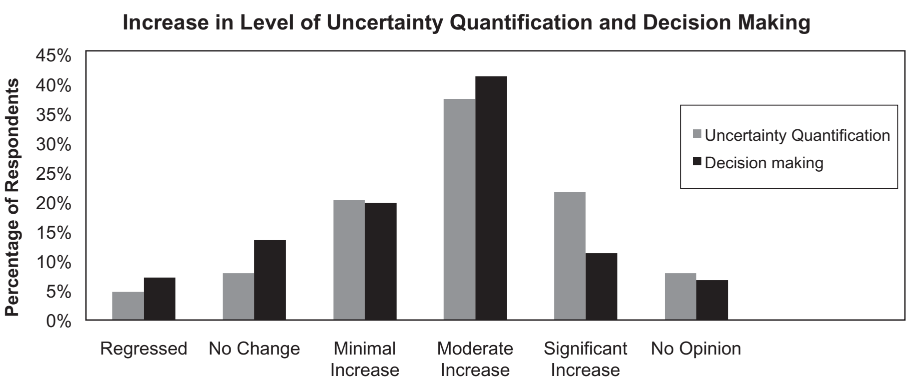
Again, these results did not differ significantly by decision-making level.

3.4 Uncertainty and Decision Making

Relationship between Uncertainty Quantification and Decision Making: In order to understand the impact of uncertainty quantification on decision making, respondents were asked to summarize the degree to which both uncertainty quantification and decision making have improved in their organizations over the last five years. The results are presented in Fig. 2.

About 60% of respondents felt that there had been some increase in both the level of uncertainty quantification and decision making. Only about 10% of respondents felt that the ability to quantify uncertainty had either regressed or not changed. Yet, twice that number felt the same way about their organization's decision-making ability. Likewise, over 20% of respondents reported a significant increase in the ability to quantify uncertainty. But, only half that number felt decision-making ability had kept pace. This fact, in conjunction with the lack of support to further improve uncertainty quantification seen in Table 5, suggest that our sharp focus on quantifying and measuring risk may not be leading to proportional improvements in decision making.

Impediments to Improvement: Respondents were asked to identify the most important obstacle in their organization to improved uncertainty quantification and decision making. The results for those respondents that had an opinion are presented in **Fig. 3**. Respondents felt that the most significant obstacle to improved uncertainty quantification was a lack of time, with lack of management understanding a close second. When it comes to decision making, respondents felt that lack of management understanding was by far the most significant impediment. Interestingly, this assessment changed little when considering only respondents that identified themselves as decision makers. This suggests that uncertainty quantification is viewed as a modeling exercise that can be understood by management, but takes significant time to implement. In the case of decision making, on the other hand, it seems as though management is less clear as to how they should incorporate probabilistic modeling into their decision making process: they understand the uncertainty quantification, but not what to do with it.



Level	Uncertainty	Decision Making
Regressed	5%	7%
No Change	8%	14%
Minimal Increase	20%	20%
Moderate Increase	37%	41%
Significant Increase	22%	11%
No Opinion	8%	7%

Fig. 2. Change in Uncertainty Quantification and Decision-Making Abilities Over the Past Five Years

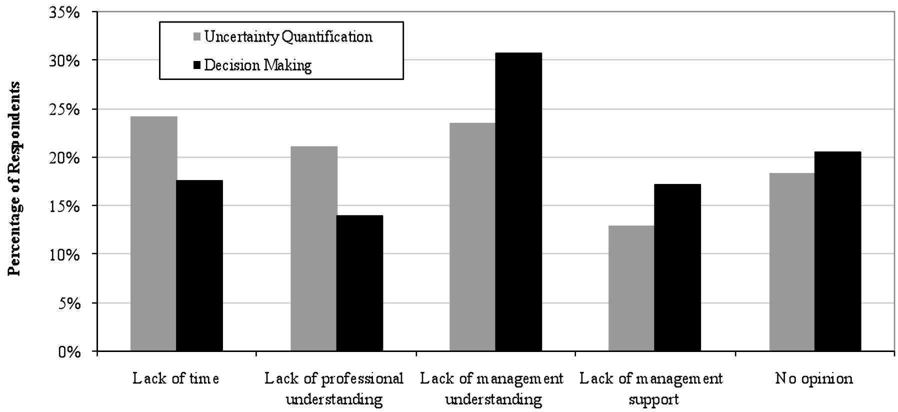


Fig. 3. Most Significant Obstacle to Improvements in Uncertainty Quantification or Decision Making

Where to Improve: Finally, in an open-ended question, respondents were asked what single area of their organization's uncertainty-quantification and decision-making processes they would most like to change. Two areas were overwhelmingly mentioned the most often: speed and consistency. Respondents would like to ensure consistency in the evaluation among projects, divisions, etc., and reduce the time to reach a decision. Communication, training, and data quality were also mentioned as important areas for improvement.

4. DECISION-FOCUSED UNCERTAINTY QUANTIFICATION

We find the survey results quite interesting. Why is it that an increase in the ability to quantify uncertainty has not produced a similar increase in decision-making ability? Why is there not a ground swell of support to further increase uncertainty quantification and forecasting abilities? Has the focus on uncertainty quantification come at the expense of consistency, as different groups apply different methods, and timeliness? Is the SPE's focus on uncertainty quantification and forecasting, via forums and workshops, benefiting the industry? Why does there continue to be a lack of focus on decision making? We believe that a partial answer to these questions has to do with the fact that better uncertainty quantification techniques will not necessarily lead to improved decision making. In this section we use the survey results as both context and motivation to suggest a framework for improving decision making and uncertainty quantification.

4.1 Uncertainty Quantification

Uncertainty quantification is not synonymous with decision making. In fact, uncertainty quantification, or reduction, creates no value in and of itself. Rather the objective is to make a good decision, which may require the assessment of uncertainty. For example, suppose you recently entered a drawing for a one-week, all-expenses-paid trip for two to Hawaii from a very reputable company (no strings attached). You just received a phone call telling you that you have won and that you can take the trip anytime during the next year. Should you decide to claim the prize? Sure. Why not? But, are you certain of how much you will enjoy the vacation? No. Can you imagine a scenario where you wish you would not have taken the vacation? Certainly! For example, suppose a tropical cyclone strikes the islands while you are there. Yet, it is clear that you should accept the prize. So, here is a situation where we must make a decision under uncertainty, but the best course of action is clear. Or, consider this example. Suppose you own your own home, which is your most significant financial asset. Do you carry fire insurance? Probably. Before purchasing this insurance did you build a model to better estimate the chance your home would be destroyed by fire? No. Could you have done this? Sure. Then why didn't you? Because for most of us there is no decision to be made; our mortgage contract requires that we carry fire insurance. No decision—no need to quantify uncertainty.

Uncertainty quantification creates value only to the extent that it holds the possibility of changing a decision that would otherwise be made differently. Uncertainty without a decision is simply a worry. Likewise, once the decision is clear, further quantification of uncertainty is a waste of resources and only serves to obfuscate the situation. For example, suppose your company is considering drilling a well whose value is uncertain; there is an 80% chance it could be worth USD 10 MM after drilling costs, and a 20% chance it could be worth USD 100 MM. Thus, the outcome is highly uncertain, but the decision to drill is clear. Reducing this uncertainty cannot alter the best course of action.

We often hear people in the industry speak of reducing uncertainty by building a model. Modeling uncertainty does not reduce it. Rather, the model is an explicit representation of the uncertainty that is already implicit in the decision problem. Uncertainty can only be reduced or altered by our choices—not simply our decision to recognize it formally.

4.2 Decisions versus Outcomes

If we are to improve decision making, we must first be clear about what a decision is, and second what it means to make a good decision.

A *decision* is an irrevocable allocation of resources, not a mental commitment to follow a particular course of action (Howard, 1966). Some decisions, such as drilling a well, are truly irrevocable. Others, such as entering into a partnership with another company, can be revoked only at some cost.

A *good outcome* is a result that is highly valued by the decision maker. A good decision is one that is consistent with the decision maker's beliefs, altrenatives, and preferences. In short, a good decision is a logical decision (Begg and Bratvold, 2002; Howard, 1966). Unfortunately, good decisions do not always produce good outcomes. For example, drilling a particular exploration well may be a very good decision, but still result in a dry hole. Likewise, poor decisions may be followed by good outcomes.

4.3 Decision Analysis

Decision analysis is a systematic procedure for transforming opaque decision problems into transparent decision problems by a sequence of transparent steps (Howard, 1966;

Howard, 1988). The goal of any decision analysis should be to provide insight to decision makers such that the best course of action is clear and *they* can make the best choice. Every activity pursued by the decision analyst should be undertaken with this in mind. For example, the generation of a probability distribution is not the end product of a decision analysis, since insights do not equal numbers. Rather, the end product, and the purpose of engineering analysis, is a "knowing what to do" on the part of the decision maker.

It is also important to stress what decision analysis is not. Decision analysis is not a procedure whereby one builds a large simulation model and places probability distributions on every input, in an effort to determine the probability distribution of some output. This is in fact an abdication of responsibility, as the "decision analyst" no longer needs to think carefully about the decision problem and identify the most important or key uncertainties—the uncertainties that could cause a decision switch. A case in point is the increase in computing power, by a factor of 100 million, that has taken place since the inception of decision analysis in the late 1960s. We do not believe that decision-making quality has increased in tandem. In fact, in our opinion, the clarity of recommendations may have decreased with the adoption of sophisticated Monte Carlo simulation programs because decision makers are now presented with dozens of probability distributions with no insight into the key aspects of their problem. Decision analysis is also not a cookbook or series of boxes that must be checked before a project is approved. This is perversion of the original intent, which was insight and clarity—not control.

That being said, a systematic process can facilitate insight generation. A decision analytic framework that we find particularly useful and relevant to the current discussion is the **decision analysis cycle** (Matheson and Howard, 1968; McNamee and Celona, 1990), depicted in Fig. 4.

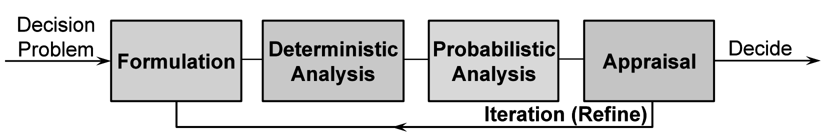


Fig. 4 Decision Analysis Cycle

The objective of each phase is described below.

Formulation. Frame or bound the decision problem, identify the alternatives and uncertainties, develop a value model, and roughly assess probabilities. This step is very important as it sets the context for all that follows.

Deterministic Analysis. Roughly assess uncertainties and identify key uncertainties via the application of various sensitivity analyses such as "tornado diagrams."

Probabilistic Analysis. Assess probability distributions, including dependencies, for the key uncertainties. Assess risk attitude. Determine the best alternative.

Appraisal. Analyze sensitivity-to-probability to determine whether changes to some set of assessments could change the optimal action. Calculate the value of gathering additional information.

The decision analysis cycle is iterative. If further assessments are required or profitable information-gathering programs exist, then this information should be gathered and the cycle repeated. Otherwise, the decision should be made. The decision model is complete when further refinements could not change the recommended course of action. This is quite different from many "study-based" processes that we have observed. First, study-based methodologies tend to be linear—great detail is built into the model from the start rather than adding detail in important areas when needed. The results of this model (e.g., a reservoir model) are then passed to the next technical discipline (e.g., facilities), and so on. No accommodation for learning or refinement is included. Second, there is no stopping rule when performing a study or making a forecast—which can always be made a bit better. Finally, the decision-analysis cycle is decision-focused rather than valuation-focused. This subtle distinction is critical. In a valuation-focused framework, one seeks to determine the absolute value of each alternative, rather than its relative value, as in a decision-focused framework. Recall, the goal is to make a good decision, which only requires that one understand which alternative has the highest value—not its value per se. One can be clear about what to do, but still not be certain of what will happen.

Finally, we need to say a few words about model complexity. In our experience, companies tend to build too much detail into their decision-making models from the start and focus too much energy on specific cases or particular inputs such as operating costs. A distinction that we have found useful is cogency versus verisimilitude (Howard, 2007). Cogency is having the property of being compelling. Verisimilitude means being true to life. We seek cogent decision models, rather than models exhibiting verisimilitude. Ron Howard has proposed a very helpful analogy to explain this concept (Howard, 2007). Consider model-train building. What makes a very good model train? One that is true to life. For example, an average model train might include a bar car. A good model train might include a bar car with people. A very good model train might show the people holding drinks. In an award-winning model train, you would be able to tell what kind of drinks the people were holding—for example, martinis with olives. Yet, inside a world-class model train, you would be able to see the pimento inside the olive!

Decision analysis is not about building model trains. Rather we seek to provide insights to decision makers regarding critical decisions. Rarely does this require "pimento-level" modeling detail. Again, this level of modeling detail is really a shirking of responsibility on the part of the decision analyst who either will not or cannot build a model that includes only the most salient factors. Building in detail is easy. Building in incisiveness is hard work. As Howard (1980) has written,

"…the real problem in decision analysis is not making analyses complicated enough to be comprehensive, but rather keeping them simple enough to be affordable and useful."

5. RECOMMENDATIONS FOR THE FUTURE: DECISION-FOCUSED UNCERTAINTY QUANTIFICATION

We close with some recommendations for future innovations regarding decision making and uncertainty quantification in the oil and gas industry.

Decision-Focused Uncertainty Quantification: First and foremost, our uncertainty quantification methods must be decision-focused. Modeling detail, including uncertainty quantification, should only be included if it helps separate the value of the alternatives under consideration. We should demand, for example, that purveyors of subsurface software demonstrate how these systems improve decision making—not simply how they enable the quantification or reduction of uncertainty.

Iterative Modeling and Decision-Making Processes: The industry needs to move away from the linear modeling and decision-making processes currently in use and should instead put in place iterative modeling and decision-making processes, like the decision analysis cycle (Fig. 4). For example, the use of "fit-for-purpose" reservoir models, integrated with facilities and economics models, would greatly speed decision making (Begg and Bratvold, 2002).

As represented in our survey results, many engineers and geoscientists do not believe there is enough time to follow a decision-analysis approach. Given that companies will find time for value creating activities, one way to address this concern is to make sure the process adds value. One way to achieve this is to ensure that we are working on the right things at the right time. As Peter Drucker has said, "there is nothing as inefficient as very efficiently doing the wrong things." The decision-analysis cycle is a process that ensures only decision-relevant activities and modeling are pursued—this will increase the value of analyses and reduce the time to complete them.

Value of Information: Increased use of value-of-information (VOI) methodologies would speed analyses, reduce cycle times, and produce greater insights. VOI focuses the analysis on the most critical pieces of information and modeling. Based on our experience (Bratvold et al., 2007), the industry spends lavishly on data gathering, modeling, etc., with very little understanding of the value of these activities.

Training and Education: Companies should ensure the consistent definition and use of uncertainty quantification and decision-making methods. This can be facilitated through the training of management and professional staff, which will build a level of comfort and familiarity that should both increase and improve the use of the decision-analytic methods.

We believe that in addition to professional training, the industry should encourage academia to better train engineers, particularly undergraduates, in decision making (Hazelrigg, 1994). Engineering is a decision-making disciple (called design), but we simply do not train engineers in decision making. In fact, we spend more time teaching them to manipulate seldom-used mathematical formulas or to write computer programs in arcane languages than we do teaching them to make high-quality decisions. While this is true in all engineering disciplines, it appears to be particularly acute in petroleum engineering (Bratvold and Begg, 2006).

Taking Our Own Medicine: We also believe that we, as decision analysts, need to work on making our methods more natural and easier for decision makers to understand. This includes both the tools and the language used to describe them (Howard, 2004). As soon as what we do is perceived as being different or strange, we are placed on the outside and in the position of having to justify our work. We would be much more effective if we sought to better integrate our methods and processes into existing workflows. This includes thinking very hard about what decision makers really need to make good decisions and making sure we provide it.

Better Professional Support: Finally, we would like to see the oil and gas industry offer forums and workshops with a decision-making focus, rather than simply quantifying uncertainty and risk.

ACKNOWLEDGEMENTS

The authors thank Ron Howard for his assistance with the survey design and his words of wisdom and clarity of thought

The authors thank the following individuals for testing an early version of this survey: Steve Begg, Gardner Walkup, Eivind Damsleth, Jitendra Kikani, Emilio Nunez, David Skinner, and Greg Bean.

The authors thank the following SPE Technical Interest Groups (TIGs) and local chapters for encouraging their members to participate in the survey. TIGS: Reserves and Economics, and Reservoir Management; Local chapters: Bergen, Caracas, Gulf Coast, Oslo, Southwest Texas, Stavanger, and Trondheim.

Finally, the authors gratefully acknowledge the individuals that were kind enough to take the survey and provide their feedback.

REFERENCES

Begg, S. and Bratvold, R., 2002. The Value of Flexibility in Managing Uncertainty in Oil and Gas Investments. SPE Annual Technical Conference and Exhibition. San Antonio, Texas. Paper SPE 77586.

Bratvold, R.B. and Begg, S.H., 2006. Education for the Real World: Equipping Petroleum Engineers to Manage Uncertainty. Annual Technical Conference and Exhibition. San Antonio, Texas. Paper SPE 103339.

Bratvold, R.B., Bickel, J.E. and Lohne, H.P., 2007. Value of Information in the Oil and Gas Industry: Past, Present, and Future. Annual Technical Conference and Exhibition. Anaheim, California. Paper SPE 110378.

Hazelrigg, G.A., 1994. Rethinking the Curriculum: Is Today's Engineering Education Irrelevant, Incomplete, and Incorrect? Prism. December: p. 56.

Howard, R.A., 1966. Decision Analysis: Applied Decision Theory. In: D.B. Hertz and J. Melese (Editors), Proceedings of the Fourth International Conference on Operational Research. Wiley-Interscience, New York, NY, pp. 55-71.

Howard, R.A., 1980. An Assessment of Decision Analysis. Operations Research, 28(1): 4-27.

Howard, R.A., 1988. Decision Analysis: Practice and Promise. Management Science, 34(6): 679-695.

Howard, R.A., 2004. Speaking of Decisions: Precise Decision Language. Decision Analysis, 1(2): 71-78.

Howard, R.A., 2007. The Foundations of Decision Analysis Revisited. In: W. Edwards, J. Ralph F. Miles and D.v. Winterfeldt (Editors), Advances in Decision Analysis. Cambridge University Press, New York, NY, pp. 32-56.

Matheson, J.E. and Howard, R.A., 1968. An Introduction to Decision Analysis. In: R.A. Howard and J.E. Matheson (Editors), The Principles and Applications of Decision Analysis. Strategic Decisions Group, Menlo Park, CA, pp. 17-55.

McKenna, M.G., Wilczynski, H. and VanderSchee, D., 2006. Capital Project Execution in the Oil and Gas Industry, Booz Allen Hamilton, Inc.

McNamee, P. and Celona, J., 1990. Decision Analysis with Supertree. The Scientific Press, South San Francisco, California.

Merrow, E., 2003. Taking on the Cult of Mediocrity. Upstream, 23 May.