Decisions, Decisions…

Michael Stefanovic P.Eng., PMP, MBA, Principal, Procept Associates Ltd.
Ingrid Stefanovic, Ph.D., Director Centre for Environment, University of Toronto

Introduction

> "If you have made a decision that was entirely based on factual information, you have not made a decision; it was made for you by the facts." (Dr. Elliott Jaques)

Decision making is a human process: inasmuch as they are made under conditions of uncertainty, decisions require human judgment. Sometimes, that judgment can be based upon our "gut feeling" which ideally arises on the basis of learning from past experience. For most decisions that are simple, this "gut feeling" is adequate. However, with increasing uncertainty and/or a growing number of independent variables, decisions become more complex and our intuitive judgments become less reliable. At that point, we require reliable methods and tools to help us make wiser choices between alternate courses of action.

"We have done a Monte Carlo simulation of your performance in 5 years. You're fired."

The first part of this paper provides an overview of a number of significant, quantitative methods that are available to us in the process of decision making. The second part challenges the objective validity of these methods, by showing how taken for granted values and beliefs must be factored into this process. In conclusion, we provide a few, central guidelines for more informed decision making practices that may incorporate quantitative methods, while carefully accounting for their limitations.

Part 1 - Quantitative Methods for Decision Making

Decision Making Matrix

A decision making matrix (Exhibit 1) can be an effective way to choose between, or to rank competing alternatives.

Originally published as a part of 2005 PMI Global Congress Proceedings – Toronto, Canada

Criteria / Altern. / Relative Weights	A	B	C	D	E	Total Score/Rank
Altern. / Relative Weights						
1	Score	Score	…			**Sum of Weight X Score/Rank**
2						
3						
4						
Etc…						

Exhibit 1 – Decision Making Matrix

The process for using the decision making matrix can be as follows:

1. Identify viable alternatives.
2. Identify criteria that are to be used for evaluating the alternatives.
3. Assign relative weight (1-10, with 10 being the most important) to each criterion. Note that more than one criterion may have the same weight.
4. Score each alternative for each criterion (again 1-10, with 10 being the best.)
5. For each alternative, multiply the score with the corresponding criteria weight and add these multiples in the last column. This is the total score for each alternative.
6. Choose the preferred alternative based on the total score.

Sensitivity Analysis

Sensitivity analysis answers the question: "how sensitive is the end result to changes in various factors affecting it?" Accordingly, sensitivity analysis can help us to decide between alternate courses of action on the basis of those factors. For example, one set of data may suggest the validity of a particular decision but, because of the high sensitivity to changes in one or more factors, another decision may become more appealing if those factors are considered in the decision making process. Sensitivity analysis can be used effectively in combination with other quantitative methods, when input data is questionable.

Expected Monetary Value (EMV)

Expected monetary value takes into account all the possible outcomes and their probabilities, of each alternative strategy (decision.) It accomplishes this by allowing for the possibility of multiplying the possible outcomes with their probabilities and adding these multiples for each strategy. Then, the strategy with the highest (or lowest, in case of cost) EMV can be selected.

The formula for EMV (Schuyler 1993) is:

$$EMV(x) = S\ [PV(x) * p(x)],$$

where: x = possible outcome, $PV(x)$ = present value of outcome, $p(x)$ = probability of outcome.

This formula allows for the possibility that the outcomes will be in the future, thus requiring use of present values and discounted cash flow.

The Payoff Table

The Payoff table (Exhibit 2) is based upon the concept of Expected Monetary Value. Selection of the preferred strategy is simplified through the organization of the EMV calculations into a table.

Strategy	Scenario #1 25%	Scenario #2 50%	Scenario #3 25%	EMV
1	$80	$50	$120	$75
2	$80	$80	$80	$80
3	$160	$120	- $20	$95
4	$20	$40	$20	$30
5	- $20	$0	$200	$45

Exhibit 2 – Payoff Table Example

In this case, it is clear that strategy #3 should be selected, since the expected monetary value of the decision is highest here.

Decision Trees

Decision trees combine the concept of Expected Monetary Value with the concept of joint probability. This approach is useful when the possible outcomes of a decision and their probabilities are arising in sequence, as a result of risks. In these cases, the joint probability of two outcomes happening in sequence is the multiple of the probabilities of each outcome.

The best way to demonstrate the concept is through an example (Wideman, Exhibit 3).

A contractor is faced with a choice that the client has offered: a Firm Fixed Price contract with the contract price of $100,000 and a “no liquidated damages” clause; or with the contract price of $115,000 and a “liquidated damages” clause. Liquidated damages will be $50,000 if the schedule is not met. The contractor knows from experience that there is a 5% chance of missing the schedule, a 60% chance that his cost will be $90,000 and a 40% chance his cost will be $80,000

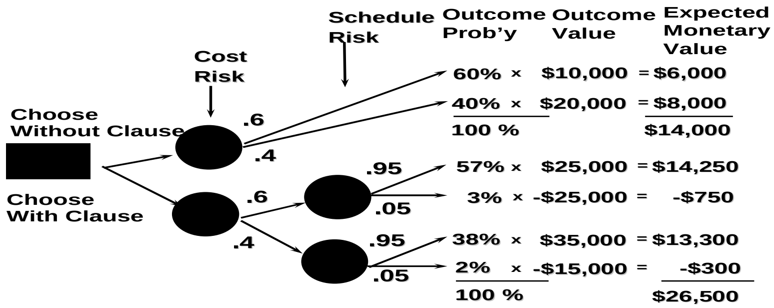

Exhibit 3 – Decision Tree Example

The decision to take the contract without the liquidated damages clause contains only the cost risk, as there is no impact if the contractor is late. Here, in order to take into account both the revenue (contract price) and cost, the outcomes need to be expressed as profit. Based on the EMV, the contractor should choose the contract with the liquidated damages clause.

Monte Carlo Simulation

The Monte Carlo Simulation was developed by John Von Neumann on the Manhattan Project during World War II. It provides a range of values and their probabilities for achieving the end result. This is useful when we are making a decision under conditions of uncertainty, because it provides a probability associated with the desired result.

It is based on the following mathematical simulation model:

f(x) = f(x1) + f(x2) + f(x3) …, where:

- f(x) is the dependent variable, the end result;
- x1, x2, x3, etc. are the independent variables, or factors affecting the end result.

For each independent variable, we can establish a range of possible values and the probability within that range. Then, we can calculate the range, and the probability distribution within the range, for the end result, by entering the ranges and the probabilities for each independent variable and choosing one value and its probability per iteration, for each independent variable, literally thousands of times.

In simpler terms, we can calculate the probability of completing a project prior to a certain date by using the schedule network as the simulation model and entering activity durations as a range of values and probabilities. Similar results can be obtained for project cost estimates.

Because of the large number of: iterations, independent variables, their values and the value probabilities, the Monte Carlo simulation is virtually impossible without computers with substantial CPUs. These have become available only in the last 10-15 years and we are seeing more and more use of this method of decision making.

Part 2 – The Human Factor

Risk Attitude

In decision making processes, we can observe three common risk attitudes: a person can be risk neutral, risk averse or a risk taker.

Someone who has a risk neutral attitude is often thought to be most "rational," since they would make their decision on the basis of the EMV, which takes into account both the outcomes and their probabilities.

A risk taker would select the strategy that has the best possible outcome, regardless of the possible negative consequences that could occur as a result of the chosen strategy and regardless of the probabilities.

A risk averse person would chose the strategy with the "best worst" or "least bad" outcome. Again, this person would ignore the fact that the best outcome of this strategy may be inferior to the best outcomes of other strategies. S/he would also ignore the probabilities of the outcomes.

If we take the example of the Payoff Table in Exhibit 2, the risk neutral person would select strategy #3 (simply because this leads to the apparently "objective" estimate of the highest EMV;) the risk taker would choose #5 because it has the highest possible positive outcome of all the strategies; and the risk averse personality would choose strategy #2, because it has the "best worst" possible outcome. Similarly, in the Decision Tree example in Exhibit #3, the risk neutral and risk taking persons would choose the contract with the liquidated damages clause, while the risk averse person would choose the one without the liquidated damages clause, since the EMV of the profit is higher with the liquidated damages clause than without it.

Of course, it is expected that each employee should rely upon their own corporate risk attitude when making decisions on behalf of her/his employer.

The Role of Bias

Personality traits affect a person's risk attitude and, therefore, influence how decisions are made. Personal biases may do the same. Ideally, the decision maker wishes to avoid bias but, inasmuch as our knowledge of the world is incomplete, pure, value-free "objectivity" is difficult to attain.

Certainly, the kinds of decision making tools that we offer above appear to be unbiased and factual, particularly because they are quantitative in nature. However, it is important to remember that a major fault with quantitative methods is lack of accurate data for input into the formulae. Often, numbers are "best estimates" that are based on faulty judgments. It can be dangerous, under such circumstances, to substitute our "gut feelings" with numbers and then proceed to take these numbers as representative of accurate data in our utilization of these mathematical models.

We must keep in mind that even the way that we use our everyday language requires that we rely upon *unstated assumptions.* Christina Chociolko (1995) asks us to imagine that an expert is asked to estimate the lower bound of the static failure pressure of a nuclear power plant. The expert replies that there is no possibility of failure at pressures below 0.83 megapascals. However, damaged steel bar welding and improper concrete mix actually cause the containment to fail at 0.62 megapascals. The expert's initial estimate was based on the unstated (and mistaken) assumption that construction of the nuclear facility will have been carried out according to all legal specifications.

Many assumptions that we make in assessing risk are not unreasonable. On the other hand, it is wise to question the basis of these assumptions and a first step is to make such assumptions explicit, as much as possible, so that they can be carefully evaluated as part of the decision making process.

Other kinds of biases have been identified by psychologists and philosophers. Chociolko identifies the importance of *motivational biases* in risk assessment, which occur when someone has a direct stake in the outcome of a decision. "For example," writes Chociolko, "an engineer is likely to say that the bridge she designed is 'absolutely safe.' Similarly, a manager responsible for ensuring a well-operated and well-funded space program is unlikely to warn of the high risk of mission failure." (1995, 20.)

Structural biases occur, quite simply, when one is swayed by the way in which a problem is "structured." Energy scientist, Amory Lovins (1991, 56) reminds us that "the answers you get depend on the questions you ask." When asked to decide upon energy policy from the perspective of *supply*, Lovins points out that depleting sources of coal and oil may provide reasonable incentive to opt for nuclear technology. However, if energy policy is viewed from

Originally published as a part of 2005 PMI Global Congress Proceedings – Toronto, Canada

the perspective of *demand* instead, then recommendations would be to reduce demand through better home insulation, solar power and other alternative energy sources. The decision as to which is the appropriate option is very much structured by virtue of the way in which the problem is presented in the first place.

There are many examples of *cognitive* biases that can also be identified in the process of decision making. "Anchoring" is one such example, where a person may fail to adjust an original estimate as new or opposing evidence becomes evident. McCray et.al. (2002, 51) describe the problem this way: project managers will typically be required to establish some measures with regard to current or proposed projects. Initial estimates in these cases will, of necessity, be based upon incomplete information or simplistic approximations. The expectation is that these estimates can be refined further on, as additional information becomes available. Research shows, however, that once these initial estimates have been made, "the human tendency is to remain close to that estimate. This heuristic is called 'anchoring' and the amount or quality of subsequently gathered data does little to offset this effect." (McCray et.al., 2002, 51.) In short, "different starting-points yield different estimates, which are biased towards the initial values." (Tversky et.al., (1974, 53.)

Another example of a cognitive bias is referred to as "availability." Once again, the human tendency is for people to overestimate the frequency of more dramatic events that are easily recalled, as opposed to less dramatic (though more common) events, which are underestimated. The stronger the emotional experience, the more easily it is remembered. So, for example, a project that supported a severe budget overrun is likely to remain front and centre in one's memory, causing a decision maker to project higher expenses on future projects, despite the fact that other similar work was performed within budget. (McCray et.al., 2002, 51.)

There are many other types and variants of biases that are reported in the literature. For instance, decision makers frequently fail to consider a broad enough range of alternative options, all in the interest of saving time. The result may mean that a viable alternative has not been noted or properly considered. Certainly, it is necessary to employ "bounded rationality" in the process, i.e. lines and limits must be drawn, in order to manage complex problems. The challenge is to find ways to ensure that vital information is not excluded in the process of delimiting a range of alternative scenarios.

Decision makers may disagree in their recommendations, if there is a need to draw conclusions from incomplete technical data. However, even in those cases where the facts are not in dispute, biases and unstated assumptions may sway decision makers in their deliberations. These biases can affect how we identify viable alternatives, how we employ different criteria in evaluating the alternatives and how we decide to assign relative weights to these options.

The Importance of Value Systems

In addition to such personal biases, there are broader value systems that reflect the wider society in which one finds oneself. For instance, North American society, based upon democratic principles, often seems to support a *utilitarian ethic*. Actions are deemed to be right, generally speaking, to the extent that they tend to promote happiness or pleasure, and wrong if they tend to cause pain. Cost-benefit analysis is very much grounded in the utilitarian ethic to the extent that the aim is to maximize benefit and minimize cost.

While utilitarianism is supported by efficiency-oriented social norms, it is also the case that western society acknowledges certain limitations of such an ethic. Perhaps the strongest criticism advanced by "deontological" critics is that utilitarianism neglects the important role of individual integrity, personal responsibility and moral principles that are not subject to a quantitative measure. For instance, I may discover a $100 bill that a wealthy man has dropped upon leaving the bank machine. Being between jobs, I calculate that the loss will bring little pain to the man, for whom $100 is mere change, compared to the happiness that it will bring me. The right decision, using utilitarian reasoning, might be to pocket the $100, maximizing the overall good. The deontologist, however, who questions utilitarian values has to ask: despite the fact that your pocketing the $100 will bring greatest overall happiness quantitatively speaking, -- is it the right thing to do *in principle*? According to a deontological ethic, stealing is wrong, no matter the consequences.

Under such conditions, the deontologist will be less interested in quantifying the maximum benefit than in asking such questions as: what duties are relevant in this situation? How would we wish to be treated in a similar situation?

Originally published as a part of 2005 PMI Global Congress Proceedings – Toronto, Canada

Are we willing to universalize our rules and courses of action? In the case of the wallet, what kind of society would we be building if we supported the rightness of stealing, in any circumstances?

While decision makers may have never taken a philosophy class, the fact is that citizens adopt broader, societal value systems, even though they may not do so consciously. A fascinating book describes a public review process of the Canadian government's decision to cancel the registration of the herbicide, "alachlor." (Brunk et.al., 1991.) The same set of scientific studies on rats elicited opposing interpretations of the data and conflicting views as to whether to remove alachlor from the market. Monsanto, the herbicide supplier, argued that risks should be balanced against potential benefits of alachlor's use. Farmers agreed, playing down the risks in favour of the benefits of remaining competitive on the global market.

The government, on the other hand, explicitly rejected this utilitarian risk-benefit approach, arguing that the decision as to whether to cancel the product's registration should be based on the principle of "safety" alone. (Brunk et.al., 1991, 13.) Environmentalists and mothers of young children similarly were not interested in balancing costs and benefits but were opposed "in principle" to any herbicide with carcinogenic risks. The authors of this study conclude that their primary finding was that these varied estimations of risk "were decisively guided by different value frameworks maintained, for the most part, implicitly and without recognition by the estimators." (Brunk et.al, 1991, 25.)

Such examples show that decision making does not operate in a moral vacuum. Those who wish to proceed as if decision making were a value-neutral process are denying the impact that can be made by implicitly accepted social norms and philosophical value systems.

Even broader worldviews and paradigms:

In addition to personal biases and social values, there are broader worldviews that are deeply embedded in our culture, our language patterns and our institutions. For instance, North American and European societies support a primarily *calculative* paradigm. (Stefanovic, 2000.) Many of the quantitative methods of decision making cited earlier in this paper support such a paradigm. Criteria such as EMV assume that value is best expressed in monetary terms. In a consumer society, money becomes the measure of all things.

However, as policy analyst Leslie Paul Thiele points out, "not everything can be bought and sold in the marketplace." (2000, 552.) Even shadow pricing may inadequately capture the real meaning of many goods. "Imagine having to put a price on the love, health or life of a child or friend. For good reason," writes Theile, "we speak of these things as 'priceless.'"(2000, 552.)

Similarly, many natural goods escape such calculative paradigms. Wilderness areas and ecosystems are often thought to resist translation into market values. Certainly, a logging company can estimate the economic value of an old growth forest in terms of the lumber that is capable of being produced. However, environmentalists criticize such an essentially "anthropocentric" (human-centred) paradigm, arguing that the value of the forest must be measured not simply in terms of its economic value to human society. This is because the "intrinsic" value of the forest overrides its "instrumental value" to humans, that is simply measured in dollars.

Certainly, there can be disagreement among decision makers as to whether the value of the forest can or cannot be measured in market terms. However, it is important to recognize that different worldviews may be at the source of the dispute and until those worldviews are explicitly articulated and evaluated, decisions may frequently be stalled or be made upon inadequate information.

Conclusions and Recommendations:

Quantitative methods have an important role to play in the decision making process. Complex decisions require complex methods that aim to simulate diverse scenarios, and to incorporate a variety of possible outcomes of diverse courses of action.

Originally published as a part of 2005 PMI Global Congress Proceedings – Toronto, Canada

At the same time, it is important to recognize that biases, value judgments and cultural paradigms affect our judgments at all stages of implementation of these methods, from the moment of identifying options and strategies, to estimating risks of specific decisions.

Certainly, in articulating options, it is necessary to engage in a process of "bounded rationality," recognizing that not every possibility can be incorporated into a Monte Carlo simulation or a decision tree. However, the wise course of action includes broad consultation amongst various groups to ensure that a variety of voices, value systems and worldviews are articulated and heard. Moreover, while quantitative methods reflect the predominant calculative worldview, careful analysis, humility and sensitivity to qualitative methods of data collection can also help to ensure that "soft" issues such as values, assumptions and cultural beliefs are also incorporated into the decision making process. (Crabtree and Miller, 1999.)

References

Brunk, Conrad, L. Haworth, Brenda Lee, *Value Assumptions in Risk Assessment: A Case Study of the Alachlor Controversy*, (Waterloo: Wilfrid Laurier University Press, 1991.)

Chociolko, Christina, "The Experts Disagree: A Simple Matter of Facts Versus Values?" in *Alternatives*, Vol. 21, No. 3, 1995, pp. 19-25.

Crabtree, Benjamin F. and William L. Miller, editors, *Doing Qualitative Research*, Second edition, (California: Sage Publications, 1999.)

Farndale Keith, "Managing Project Risk," Risk Management seminar provided by Procept Associates Ltd., 1998-2005.

Lovins, Amory, "Technology is the Answer (But What Was the Question?) in G. Tyler Miller, ed., *Environmental Science*, third edition, (Belmont, CA: Wadsworth, 1991.)

McCray, Gordon E.; Purvis, Russell L., McGray, Coleen G., "Project Management Under Uncertainty: The Impact of Heuristics and Biases," in *Project Management Journal*, Vol. 32, No. 1, March 2002, pp. 49-57.

Schuyler, John R., "Decision Analysis in Projects," *PMNetwork*, Volume VII, No. 4, April 1993, pp31ff.

Stefanovic, Ingrid Leman, *Safeguarding Our Common Future: Rethinking Sustainable Development*, (Albany, NY: State University of New York Press, 2000.0

Thiele, Leslie Paul, "Limiting Risks: Environmental Ethics as a Policy Primer," in *Policy Studies Journal*, 2000, vol. 28 No. 3, pp. 540-557.)

Tversky, A., and D. Kahneman, "Judgment under Uncertainty: Heuristics and Biases" in *Science*, Vol. 185, 1974, pp. 1124-31.

Wideman, Max, *Project and Program Risk Management: A Guide to Managing Project Risks and Opportunities*, (Project Management Institute: 1991.

Originally published as a part of 2005 PMI Global Congress Proceedings – Toronto, Canada