Trade Studies with Uncertain Information

Dr. David G. Ullman, President, Robust Decisions Inc.

Brian P. Spiegel, Aerospace Electronic Systems, Honeywell

Sixteenth Annual International Symposium of the
International Council On Systems Engineering (INCOSE)
8 - 14 July 2006

Abstract

During every stage of the design process, designers trade off performance, cost, and risk in an evolutionary process whose goal is to find a satisfactory solution. This paper explores a recent method to manage the trade study process especially when uncertainty is pervasive and decisions are a mix of quantitative and qualitative information. We believe that it is possible to support a trade study process that is sensitive to the uncertainties in evolving system information, a key ingredient in managing risk, robustness, changes and spiral development. In this paper we explore what is needed to support such activities. To do so we follow an example as it gets increasingly complex and realistic. As the issues addressed increase in computational need, we make use of *Accord*, a decision support system base on Bayesian Team Support methods.

Introduction

With the increasing demand for complex and interrelated systems comes the challenges of managing the decisions being made by a team of collaborating experts, each working on a piece of the puzzle, and all vying for their share of the scarce resources. In early stage design, this process is especially challenging as there is limited knowledge, uncertainties are high, and the decisions made have far reaching effects on the directions pursued thereafter, and hence the affordability, reliability/safety and effectiveness of the final product. It is clearly more viable and less expensive to refine a design at the time that it is being conceived. Therefore efforts towards making good decisions at this stage have high payoffs.

During every stage of the design process designers trade off performance, cost, and risk in an evolutionary process whose goal is to find a satisfactory solution. This paper explores a recent method to manage the trade study process especially when uncertainty is pervasive and decisions are a mix of quantitative and qualitative information. We believe that it is possible to support a trade study process that is sensitive to the uncertainties in evolving system information, a key ingredient in managing risk, robustness, changes and spiral development.

In this paper we explore what is needed to support such activities. To do so we follow an example as it gets increasingly complex and realistic. As the issues addressed increase in computational need, we make use of *Accord*, a decision support system based on Bayesian Team Support methods

What are Trade Studies

A trade study is the activity of a multidisciplinary team to identify the most balanced technical solutions among a set of proposed viable solutions (FAA 2004). These viable solutions are judged by their satisfaction of a series of measures or cost functions. These measures describe the desirable characteristics of a solution. They may be conflicting or even mutually exclusive. Trade studies, often called trade-off studies, are commonly used in the design of aerospace and automotive vehicles and the software selection process (Phillips et al 2002) to find the configuration that best meets conflicting performance requirements.

The measures are dependent on variables that characterize the different potential solutions. If the system can be characterized by a set of equations, we can write the definition of the trade study problem as: Find the set of variables, x_i that give the best overall satisfaction to the measures:

$$T_1 = f(x_1, x_2, x_3\ldots..)$$
$$T_2 = f(x_1, x_2, x_3\ldots..)$$
$$T_3 = f(x_1, x_2, x_3\ldots..)$$

$$T_N = f(x_1, x_2, x_3\ldots..)$$

Where T_j is a target value and f(…) denotes some functional relationship among the variables. Further, the equality between the target and the function may be a richer relationship, as will be developed below. If the equations are linear, as in the production volume example used as a starting point below, then this problem is solvable using linear programming techniques. Generally, one or more of the targets is not fixed at a specific value and it is desired to make these T values as large or small as possible. These are generally referred to as cost functions and the other measures are treated as constraints.

If the situation was as described above formal optimization or linear programming methods would work and there would be no need for this paper. However, in practice needed information is:

- Uncertain - to be detailed below
- Evolving - new information is being developed that affects the trades
- Both qualitative and quantitative - at Honeywell the most important trade studies have predominantly qualitative information
- Comes from conflicting sources - in systems engineering, many people have some of the information needed; no one person has it all.
- The best choice comes from a team, building a shared mental model of the situation.

Trade studies are essentially decision-making exercises - choose an optional concept or course of action from a discrete or continuous set of viable alternatives. In the FAA Systems Handbook (FAA 2004) the decision analysis matrix (aka Pugh's method) is suggested to support the activities, but this method can not support uncertainty, a mix of quantitative and qualitative information, or teams. To manage uncertainty, the authors suggest supplementing point estimates of the outcome variables for each alternative with computed or estimated uncertainty ranges. The Standard Approach to Trade Studies (Felix 2004), an INCOSE paper from 2004 suggests a similar approach.

The NASA Systems Engineering Handbook (NASA 1995) suggests using multi-attribute utility theoretic (MAUT) or the Analytic Hierarchy Process (AHP). But, these too are not good with uncertainty, mixed information and teams. The authors suggest using probability based methods to maximize utility when uncertainty predominates, but give little detail on how to approach this.

Another approach to supporting trade study information is to use the Bayesian Team Support (BTS) methods. These methods were designed to manage the types of information itemized in the list above. In this paper we will introduce BTS and apply it to a trade study example to explore its applicability.

The Effect of Uncertainty on Trade Studies

What makes early system design and trade studies most challenging is that much of the critical information is uncertain, evolving, and may be lacking in fidelity. Further, with team members from many disciplines and with different values about what is important, information may be conflicting. These terms, "uncertain", "evolving", "fidelity" and "conflicting" permeate this paper and thus need clarification.

There are two types of **uncertainty**. The first, **variability** (i.e., stochastic uncertainty, irreducible uncertainty, or common cause variability) is the result of the fact that a system can behave in random ways. The weather will change, material properties are variable, and there will always be chip junctions failures. In general, even though some portion of variation can be controlled (e.g., insulation from weather changes) there is always variation that is either uncontrollable or too expensive or difficult to warrant controlling.

The second type of uncertainty results from the **lack of knowledge** about a system (i.e., subjective uncertainty or state of knowledge uncertainty). It is a property of the team members' cumulative experience and the amount of time they have spent on the current or similar concepts. Both types of uncertainty are direct causes of risk - as, in a world with no variability and perfect knowledge, there would be no risk.

Typically, probability theory has been used to characterize both types of uncertainty. Variability is usually analyzed using the frequentist approach associated with traditional probability theory. However, traditional probability theory is not capable of capturing lack of knowledge uncertainty, which, in early design is a large cause of risk. One method for managing lack of knowledge uncertainty is Bayesian methods as will be discussed later.

During the design process information is **evolving.** It begins with customers' criteria and matures to the final drawings, specifications and code. Through this development, the trade offs and risks are changing as the systems evolve. Managing this evolution is crucial in systems as changes in one system will affect others. Sometimes these interactions are missed leading to rework, compromised performance or system failure.

As part of design activities, experts run simulations to predict performance and cost. Early in the design process these simulations are at low levels of fidelity, some possibly qualitative. **Fidelity** is the degree to which a model or simulation reproduces the state and behavior of a real world object. To increase fidelity requires increased refinement and increased costs to the project. Generally, with increased fidelity comes increased knowledge, but not necessarily so as it is possible to use a high fidelity simulation to model garbage and thus do nothing to reduce uncertainty. Often, especially in early trade studies, there are no formal simulations and all or most of the evaluations are qualitative. These evaluations are no less valid than detailed simulations. In fact, it has been argued that gut-feel is the key to good decisions (Klein 1996, Gladwell 2005).

Finally, the team members' interpretation of the available information may be **conflicting**. Conflicting interpretations occur naturally due to differences in background, role in the project, interpretation of the information, expertise, and problem solving style. Conflicts are not good or bad, just different interpretations of the available information.

Traditional solution methods can not take these uncertainties into account. If they are small compared to the actual values then these methods can be used assuming the uncertainties exist to find a solution and then the take into account the uncertainties using sensitivity analysis. However, if the uncertainties are significant, another philosophy needs to be followed.

Details on Bayesian Team Support

Bayesian decision theory has its roots in the work of an obscure 18th century cleric (Rev. Bayes) who worried about how to combine evidence in legal matters. However, its modern form traces to the work of John Von Neumann, mathematician and computer pioneer, in the 1940s; and J. Savage in the 1950s. In Savage's formulation (Savage 1955), a decision problem has three elements: (1) beliefs about the world; (2) a set of action alternatives; and (3) preferences over the possible outcomes of alternate actions. Given a problem description, the theory prescribes that the optimal action to choose is the alternative that Maximizes the Subjective Expected Utility (MSEU). Bayesian decision theory excels in situations characterized by uncertainty and risk, situations where the available information is imprecise, incomplete, and even inconsistent, and in which outcomes can be uncertain and the decision-maker's attitude towards them can vary widely. Bayesian decision analysis can indicate not only the best alternative to pursue, given the current problem description, but also whether a problem is ripe for deciding and, if not, how to proceed to reach that stage.

As classical statistics revolutionized the *discovery* of knowledge in the early 20th century, so Bayesian decision theory is revolutionizing the *application* of knowledge in the 21st. This revolution is already underway. Microsoft, for instance, is investing heavily in the use of Bayesian methods that improve the filtering and management of information, daily barraging PC users. Microsoft's first release (Mobile Information Manager) filters and prioritizes email messages (Business Week 2001). Bayesian methods form the basis of:

- Most major anti-spam tools
- All speech recognition tools
- Medical diagnosis
- Counter terrorism defenses
- Robotics and navigation

There is a well-known problem in applying Bayesian decision theory: until recently there was no known sound way to fuse information from multiple information sources.

RDI developed and patented methods solve this problem, extending the application of Bayesian decision analysis to multi-source decision-making. RDI's methods also significantly extend the scope of Bayesian modeling to problem-formulation, previously only available in informal decision-making methods that provide no analytical support. We call this extension **Bayesian Team Support, BTS**.

As stated before, a Bayesian decision model, as specified by Savage, has three elements: (1) a set of beliefs about the world; (2) a set of decision alternatives; (3) a *preference* over the possible outcomes of action. Belief modeling must, first of all, be simple and intuitive. Complex models that require vast amounts on precisely specified information may be theoretically attractive, but are useless in real-world problems. We model belief about *how each evaluation by an expert provides evidence about an alternative*. Statement about belief can be as simple as "The Delta will lift the payload". Often the source will be uncertain about whether such a statement is true or not (e.g., the source of the information may not be reliable, the identification not positive, etc.). RDI's methods provide simple graphical interfaces for stating not only current belief about a statement, but also the amount of *certainty* in the observation. We model the **Level of Evidence** as the belief, and the **Level of Certainty** as the relationship between the belief and the actual state of the matter. This model provides the formal basis for combining beliefs from multiple sources into an overall assessment of the threat of each actor (Robust Decisions 2005).

The final major component of RDI's collaborative decision modeling is its preference model. A preference model corresponds, roughly, to a set of objectives or criteria that are used to judge the alternative solutions.

RDI has commercialized BTS in *Accord™,* a product that provides decision support. A key selling point of *Accord* is its graphical nature. During the entire communication, both information input and results output are in a single window as shown in Figure 1.

To explore how *Accord* can support trade studies when uncertainty is significant, a simple example was studied.

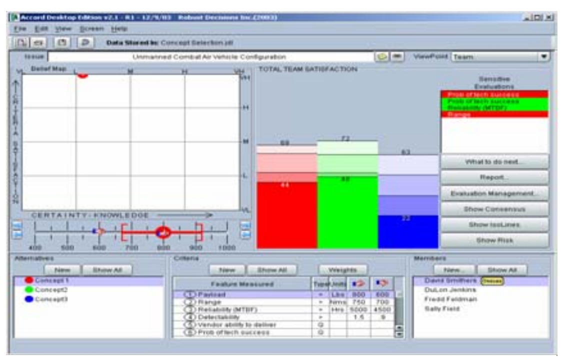


Figure 1, Accord Example

A Production Volume Example

Consider a simple example of a trade study taken from a textbook on optimization (Arora 1989). A company manufactures 2 machines, x_1 and x_2. It wants to find the number of x_1 machines and x_2 machines to manufacture so that profit will be maximized. It is known that:

- Profit on machine x_1 is \$400 and profit on machine on x_2 is \$600.
- Using available resources it takes twice as much time to make machine x_2 as it does machine x_1.

- The company can make a maximum of 14 x_2 machines a day.
- Using available resources sales can sell up to 14 x_1 or 24 x_2 machines per day.
- Shipping can only handle 16 x_1 or x_2 machines a day.

This is a simple trade study problem with only one measure (profit) and two variables (# of x_1 machines and # of x_2 machines). Further, the way the problem is set up; there are linear relationships for the cost, manufacturing, sales and shipping. Namely:

- Profit/day = $400\ x_1 + 600\ x_2$
- $x_1/28 + x_2/14 <= 1$, for manufacturing
- $x_1/14 + x_2/24 <= 1$, for sales
- $x_1 + x_2 <= 16$, for shipping

Since all these equations are linear, this problem can be solved by linear programming methods. The equations can be plotted as shown below with x_1 horizontal and x_2 vertical and using a method like Simplex, or in this simple case by inspection, point #7 is seen to give the best profit and meet all the other goals. Thus, the company should make 4 of Type x_1 machines and 12 of Type x_2 machines. Doing this, their profit will be \$8,800/day.

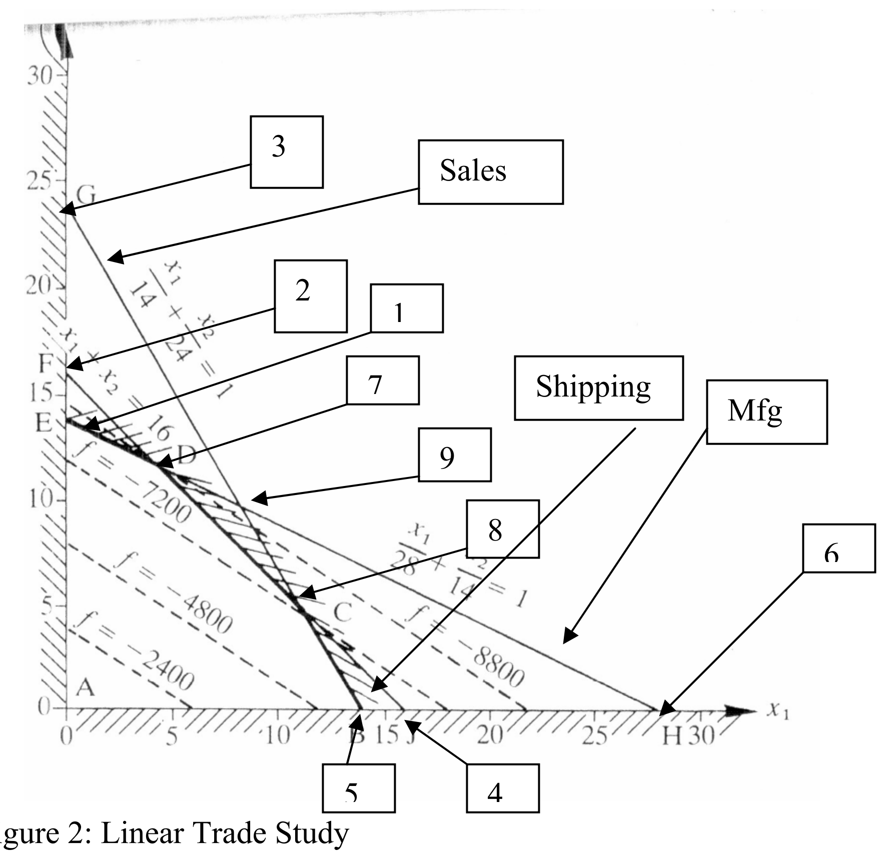


Figure 2: Linear Trade Study

This is a good textbook problem. It will be used as a basis while we explore:

- Target uncertainty
- Evaluation uncertainty
- Importance uncertainty

- Mix of qualitative and quantitative criteria
- Fusion of multiple team members' evaluations
- Determining what to do next to ensure that the best possible decision is being made.

To make this problem more interesting, assume that we explore points 7, 8 and 9 in our effort to choose the best option. In many actual trade studies, the options are discrete as the functions relating variables are unknown, or at best, uncertain.

Target uncertainty

Target uncertainty reflects flexibility in what is desired of each measure in the problem. In order to discuss target, first rewrite the equations that represent this problem as:

- Profit/day = $400\ x_1 + 600\ x_2$
- $x_1*.5+ x_2<=14$, for manufacturing
- $x_1*1.71+ x_2 <=24$, for sales
- $x_1 + x_2 <=16$, for shipping

Considering the manufacturing, sales and shipping equations first, each has been normalized to show a number of x_2 units that reflects capacity. It makes no difference if these equations are normalized on x_1 or x_2. The main point is that manufacturing thinks it can produce 14 normalized machines, sales can sell 24 and shipping can ship 16. But, how accurate are these targets? For this example, let us assume that these normalized target values are our best guess. Further, if manufacturing, for example, is asked to produce 15 normalized machines, this can probably be worked in. Maybe even 16 can be accommodated based on what is known about manufacturing. However, at some volume, overtime, additional equipment, or some other painful change will be needed. Likewise in the negative direction, at some volume less than 14, there will be idle people or equipment. Thus, **target uncertainty** reflects the flexibility that exists in most targets to accommodate satisfying other criteria or maximizing satisfaction with the choice made. Consider buying a car, camera or house. You set a target for the cost, but then, if other features are really great, you adjust the target. The better the system is understood and less flexibility possible, the lower the target uncertainty.

We will model each of the targets as a simple linear utility function. Target uncertainty can be characterized by two values, a delighted value and a disgusted value. For example, .a profit of $10,000 will delight the company and one of $7,500 will disgust them. This is more is better target as shown in Figure xx.

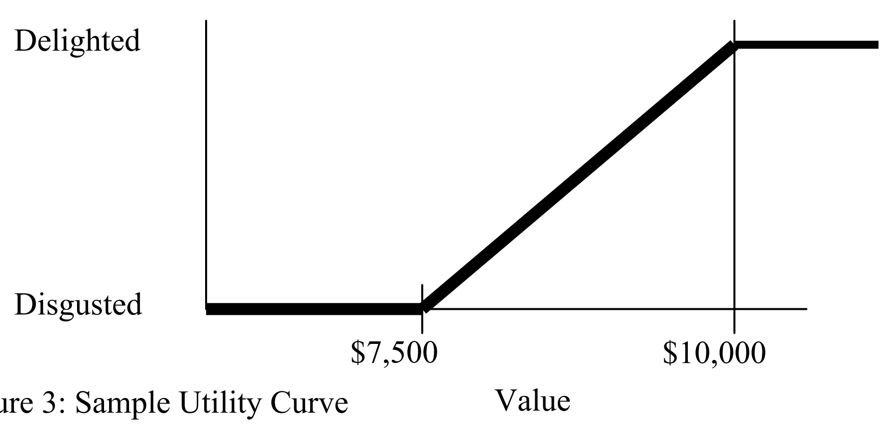
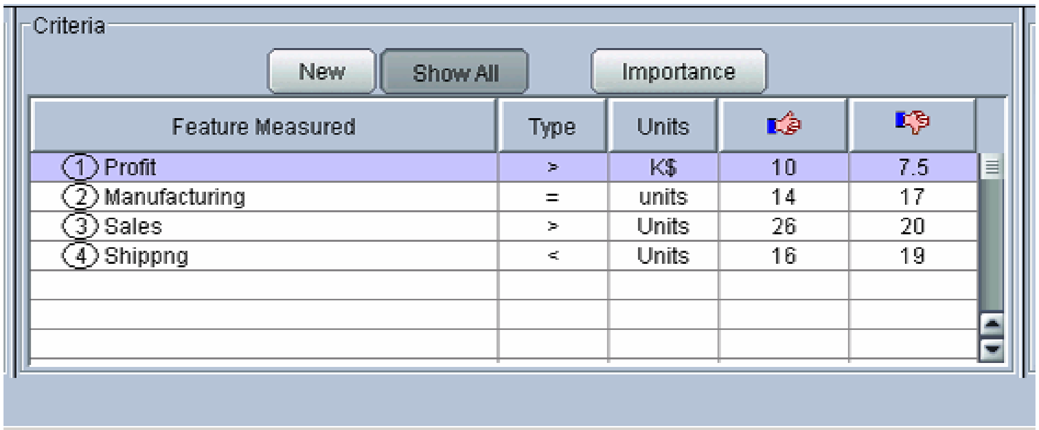


Figure 3: Sample Utility Curve

Similarly:

- Manufacturing Target Uncertainty: As described above, delighted at 14 x_2 units, disgusted at 11 and 17. This is referred to as a specific target best and the utility curve is a two sided distribution.
- Sales Target Uncertainty: Sales works on commission so the more sales the better. They will be delighted at 26 x_2 units, disgusted at 20
- Shipping Target Uncertainty: Shipping is lazy so the less they have to do, the better. They will be delighted at 16 x_2 units, disgusted at 19.

A screen shot from *Accord*, Figure 4, shows this information entered as Criteria. Note the "Type" symbols indicating the shape of the utility function.



Feature Measured	Type	Units		
1 Profit	>	K$	10	7.5
2 Manufacturing	=	units	14	17
3 Sales	>	Units	26	20
4 Shippng	<	Units	16	19

Figure 4, Screen shot of the criteria and members area

Evaluation and Viewpoint Uncertainty

Next, consider the equations that are used represent the measures. For example, the equation for manufacturing is $.5 * x1 + x2 \leq 14$. We have already discussed the uncertainty in the target, 14 units, and now focus on the terms on the left side of the equation. **Evaluation uncertainty** is the fidelity with which the equation represents reality. This equation has been written as a linear equation, but it is difficult to believe that the relationship is that simple, and that the coefficient is .5. In fact, the actual relationship may be more complicated and the coefficient some other value. Even more challenging is that the relationship may be different to different functions within the organization or that the relationship is completely unknown.

For the example, assume that the uncertainty in the equations may be as much as 10% of the nominal value calculated. If, for example, x_1=8 units and x_2 = 10 units (point 9) then, using the equation above, manufacturing can produce 8*.5+10= 14 units. If the equation is 10% high, then it will estimate 17 units (rounded to the nearest whole unit), and if low it will estimate 11 units. This may seem like a high uncertainty. However, for production lines that are just being designed or not yet mature, this is a conservative number. The same holds for sales and shipping.

A spreadsheet, Figure 5, was used to calculate the nominal values and the +10% and –10% deviations from them.

	x_1	x_2	profit	profit +	profit -	mfg	mfg +	mfg -	sales	sales +	sales -	ship	ship +	ship -
pt #	units	units	K$			# of x_2 units			# of x_2 units			# of x_2 units		
7	4	12	8.8	9.7	7.9	14.0	15.4	12.6	18.8	20.7	17.0	16.0	17.6	14.4
8	11	5	7.4	8.1	6.7	10.5	11.6	9.5	23.8	26.2	21.4	16.0	17.6	14.4
9	8	10	9.2	10.1	8.3	14.0	15.4	12.6	23.7	26.0	21.3	18.0	19.8	16.2

Figure 5, the spreadsheet calculations

Accord merges this information with the utility information to calculate overall satisfaction (amongst other analyses) for each alternative considered (here points 7, 8, and 9). The results can be weighted for different viewpoints.

The importance of each of the measures may vary with function in the company. Some may believe that profit is really the only important measures, whereas other may want to equally weight manufacturing or sales capacity. **Importance uncertainty** reflects differences in what targets are most important to meet in finding a solution to the problem.

The satisfaction calculated by *Accord* when only profit is important (all the other measures are weighted at zero) is shown in left section of Figure 6. Here the bars represent the percent satisfaction with each of the alternatives. The results show:

- Point 9 is best, with point 7 second and point 8 last. This order is obvious from Figure 5 or from the linear trade study diagram (Figure 2).
- Point 9 is only 57% satisfactory as the company said it would be delighted at $10K which is only met with the most optimistic estimate ($10.1K). The pessimistic estimate is not far above the disgusted level.
- There is a risk of 43% that the company will not be satisfied with profit. This risk is actually an expected value of not being satisfied.

In the right half of Figure 6 the satisfactions are shown when Shipping and Manufacturing are both considered important. Here Point 7 is best, just barely. This does show that satisfaction can change with the eye of the beholder.

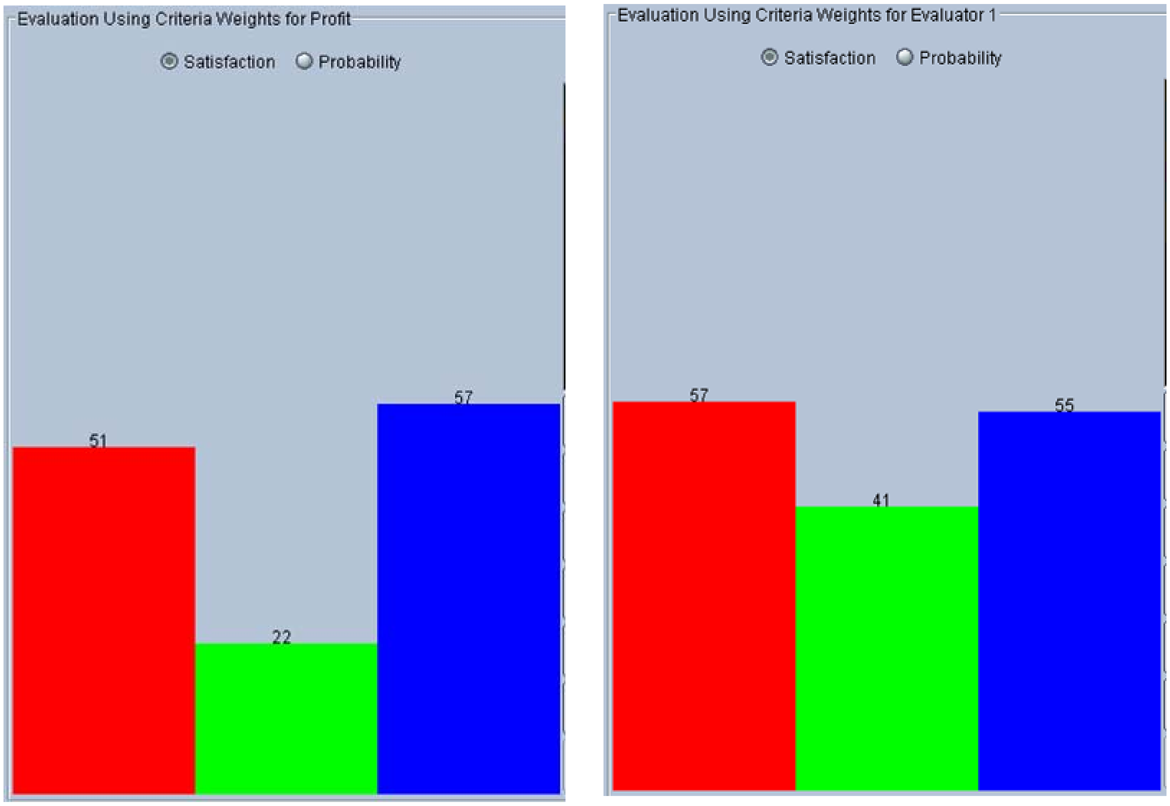
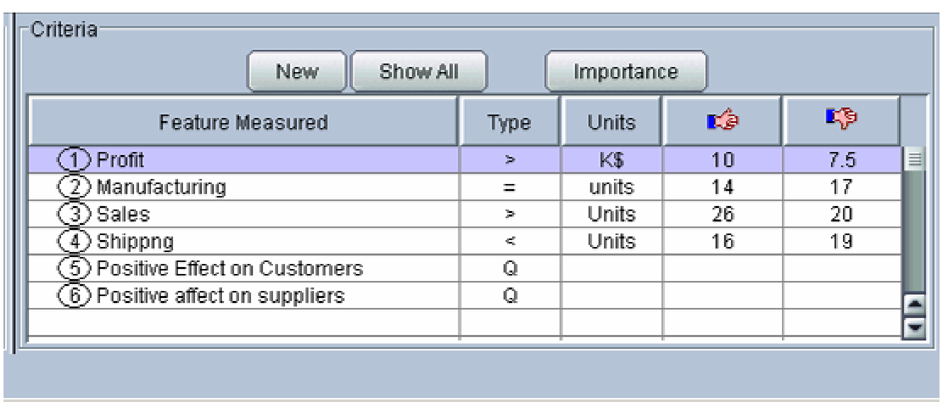


Figure 6. Early results

Qualitative criteria

Usually, not all the important features of alternatives are measurable even though good practice encourages us to measure everything. The reality is well summed up by a quotation attributed to the Noble Laureate Frank Knight. After reflecting on Lord Kelvin's statement, “When you cannot measure it…your knowledge is of meager and unsatisfactory kind”, Dr. Knight said “ Oh, well, if you cannot measure, measure anyhow”. The reality is that o refine something that is not readily measurable requires time and effort that may not be available.



Feature Measured	Type	Units		
1 Profit	>	K$	10	7.5
2 Manufacturing	=	units	14	17
3 Sales	>	Units	26	20
4 Shippng	<	Units	16	19
5 Positive Effect on Customers	Q			
6 Positive affect on suppliers	Q			

Figure 7 Added qualitative criteria

In this case, some difficult to measure features are market perception (i.e. if you make too few of one product you might be perceived as abandoning that product), affects on suppliers (i.e. if you don't order parts needed for x1 the vendor may discontinue making them), etc. These qualitative measures can be added to the list of criteria in *Accord* and are denoted with a "Q" as shown in Figure 7. We will show the effect of the addition of these qualitative criteria in a moment. Qualitative criteria are evaluated using a Belief Map.

The Belief Map provides a novel, yet intuitive, means for entering/displaying qualitative evaluation results in terms of knowledge, certainty, satisfaction and belief. Belief maps offer a quick and easy-to-use tool for an individual or a team to ascertain the status of an alternative's ability to meet a criterion, to visualize the change resulting from analysis, experimentation or other knowledge increase or uncertainty decrease, and to compare the evaluations made by the team members. Each point on the belief map is <u>color coded</u> to match the alternatives and <u>numbered</u> to match the criteria.

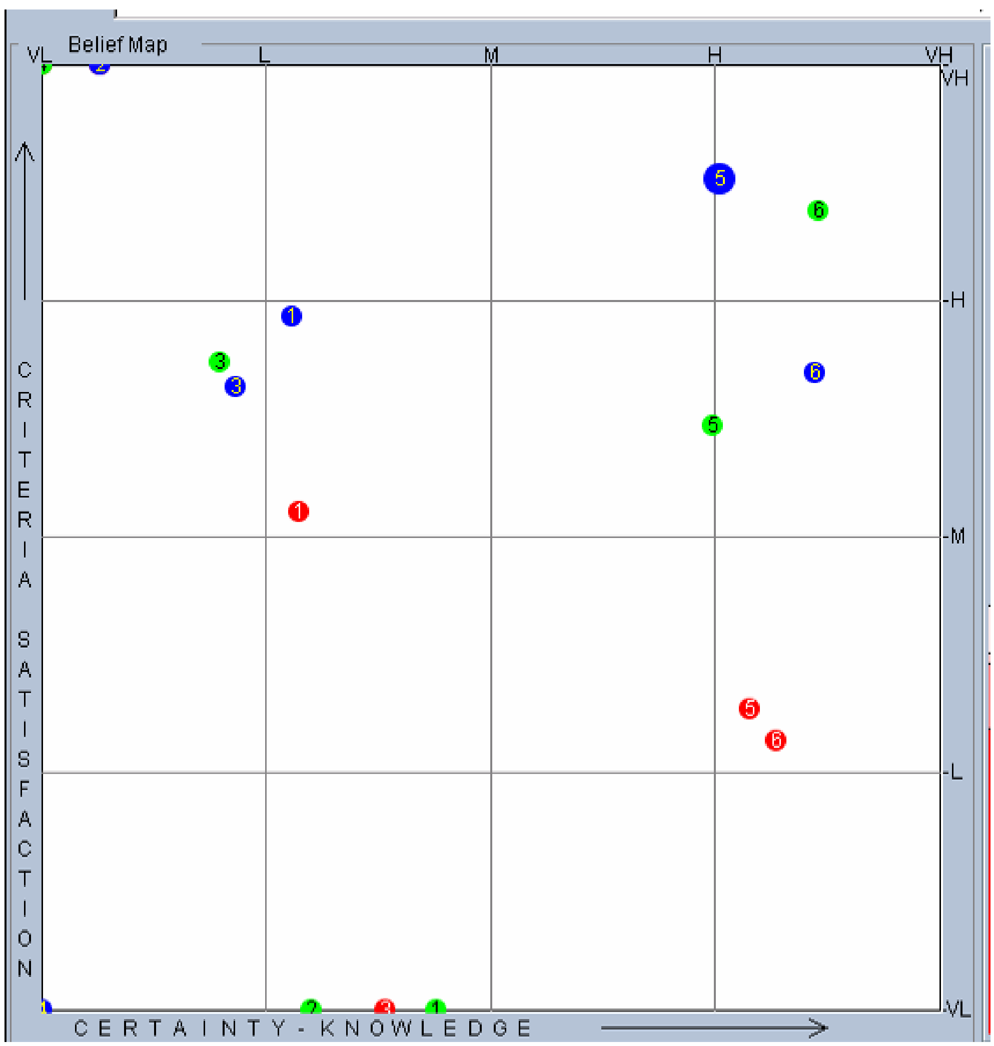


Figure 8 Sample Belief Map

For qualitative evaluations the vertical axis represents the "criterion satisfaction", how well the alternative being evaluated satisfies the criterion. This is analogous to the numerical rating given a decision matrix (aka Pugh's matrix). The horizontal axis is referred to "certainty-knowledge" as the evaluator's certainty or knowledge is the basis of the assessment.

The logic behind the belief values is easily explained. If an evaluator puts her point in the upper right corner, then she is claiming she is an expert and is confident that alternative fully meets the criterion. If she puts her point in the lower right corner, she is expert and confident that the alternative has a zero probability of meeting this criterion. If she puts her evaluation point in the upper left corner she is hopelessly optimistic: "I don't know anything about this, but I am sure it will work" - she believes that alternative meets the criterion even though she has no knowledge on which to base this belief. This is referred to as "the salesman's corner" If she puts her evaluation point in the lower left corner she is pessimistic "I know nothing, but it will be bad".. This is called the "engineer's corner" for obvious reasons

Accord changes all points on the belief map into probabilities for fusion with other evaluation information. The Belief Map for all the evaluation in the example is shown in Figure 8.

Fusion of multiple team members' evaluations

Usually, decisions are made based on the fusion of many people's knowledge and opinion. Where only one estimate may be made for profit or other import measure in most organizations, there are other models with other results that are often ignored. It is not that the one used is right and the others are wrong, it is that multiple estimates of the situation are difficult to manage. This is exasperated when the measures are qualitative because there are no numbers to fall back on.

A strength of the BTS methodology is its ability to fuse the evaluations from multiple evaluators or team members. There is not room to describe the methodology here, but the reduction of all information to probabilities and expected values allows this fusion. To demonstrate this, two additional evaluators are added to the example problem. Fusing their estimates of profit and the other measures based on other models and knowledge with what is already in *Accord*, Point 9, satisfaction grows even stronger relative to the other options.

What to do next

In *Accord* there is a "What to Do Next" analysis. This generates a report based on all the input and calculated data. Using an internal rule base, the What to Do Next analysis takes the information developed and generates an ordered list of what the decision-maker(s) should do next to improve the differentiation in satisfaction between the highest ranked alternative or the probability that the highest ranked alternative is best. The top items on the list are generally the most effective for the effort required to address them.

In the text, the "what to do next" suggestions are typically one of three types:

- Evaluation can be improved by gaining consensus on specific items. This means that the information from the various sources does not agree and formalized process to resolve the inconsistency can result in increased shared knowledge and confidence in the evaluation.

- Evaluation can be improved by gathering more information or doing more analysis on specific evaluations. Again, only those areas that can significantly affect the satisfaction level are identified.
- Refine qualitative criteria.

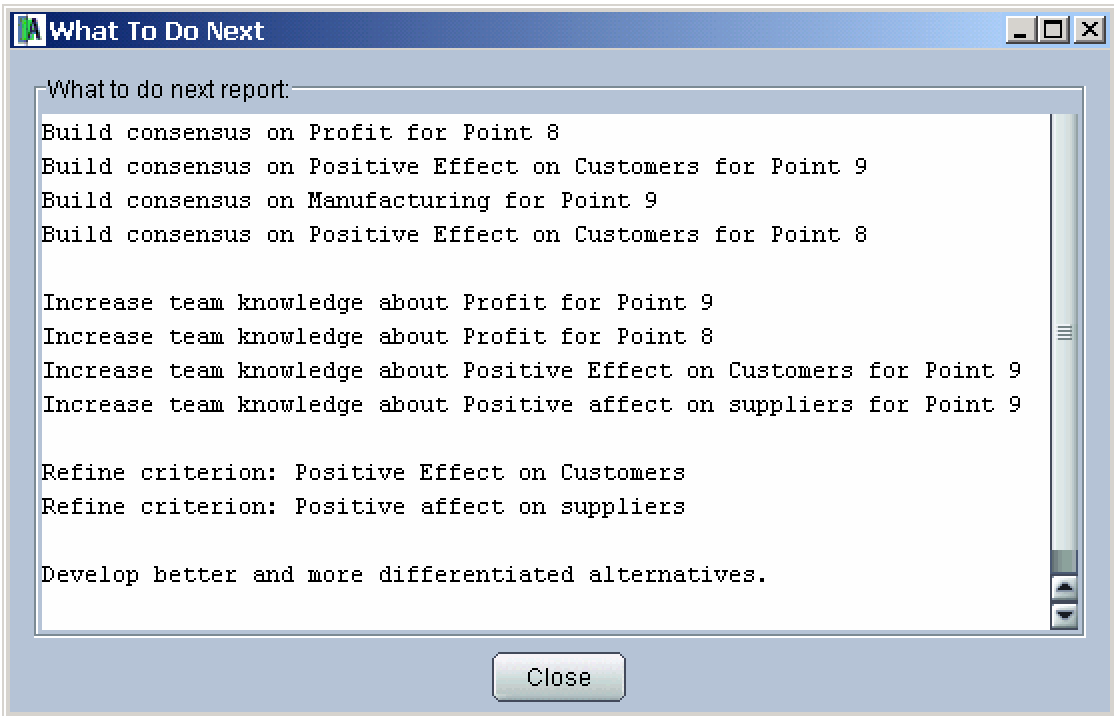


Figure 9. What to do next report

The goal of this display is to reduce the cognitive load on the decision-makers while providing them with the best possible information for making a decision. Based on this report, the team worked on the items identified.

Conclusions

For the example problem and based on the current evaluation, Point 9 is the best choice and potentially gives more profit than Point 7. There may be even a better point that has not been evaluated as suggested in the What-to-do-next report. Considering that Points 7 and 9 require 4 to 8 x_1 machines and 10 to 12 x_2 machines, it seems logical to consider other options in this range.

In general, trade studies are difficult to support especially when information is uncertain, incomplete, evolving and conflicting. Analytical methods only apply when the system is well known and they can't support multiple opinions and uncertainty. This paper has demonstrated the application of Bayesian Team Support as instantiated in *Accord* to manage a trade study. It has helped address:

- Target uncertainty

- Evaluation Uncertainty
- Importance Uncertainty
- Mix of qualitative and quantitative criteria
- Fusion of multiple team member evaluations
- Determining what to do next to ensure the best possible decision is being made.

References

FAA, *System Engineering Manual Version 3.0*, Section 4.6, Trade Studies, Federal Aviation Administration, 2004, www.faa.gov/asd/SystemEngineering/

Phillips, B. C. and S.M. Polen, Add Decision Analysis to Your COTS Selection Process, Crosstalk, April 2002

Felix A., *Standard Approach to Trade Studies: A Process Improvement Model that Enables Systems Engineers to Provide Information to the Project Manager by Going Beyond the Summary Matrix*, http://www.incose.org/so-md/ChapterMeetingMinutes/Presentations/2004NovTrade%20Study%20Brief%20-%20AFelix.pdf

NASA, *NASA Systems Engineering Handbook*, Section 5.1 Trade Studies, NASA SP-610S 1995, dcm.gsfc.nasa.gov/library/Systems_Engineering_Handbook.pdf

Klein G., *Sources of Power: How People Make Decisions*, MIT Press 1996

Gladwell M., *Blink,* 2005, Little Brown

Savage L.J., *Foundations of Statistics*, 1955 (2nd Revised edition, Dover, 1972).

Business Week, *The Ghost in the Machine*, July 31, 2001, http://www.businessweek.com/bwdaily/dnflash/jul2001/nf20010731_509.htm

Robust Decisions, Details for how we combine beliefs can be found at http://www.robustdecisions.com/bayesianmethoddecisions.pdf.

David G. Ullman is Emeritus Professor of Mechanical Design, Oregon State University, and President of Robust Decisions Inc. An active product designer, he has taught, researched and written about design and decision making over 20 years. His text, *The Mechanical Design Process*, 3rd edition, McGraw Hill, 2003, is used at many universities. His book *12 Steps to Robust Decisions* was published in 2001.He is a Fellow of the American Society of Mechanical Engineers (ASME) and founder of its Design Theory and Methodology committee. He is a registered Professional Engineer in Oregon and New York.

Brian Spiegel is the Customer Quality Manager for the Missiles & Munitions business in Defense and Space for Honeywell International located in Clearwater, Fla. Brian received his Bachelor's degree in Metallurgical Engineering from The Ohio State University. Brian is also Black Belt and Design for Six Sigma (DFSS) certified. He was recently awarded Outstanding Engineer in 2004 at Honeywell for his work applying DFSS to improve the IPD process.