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DESIGN: THE EVOLUTION OF INFORMATION PUNCTUATED BY DECISIONS

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ABSTRACT
This paper describes the author's 30 year evolution from thinking about parts, assemblies and systems, to a decision-centric view of design. The point is made that product is only as good as the decisions made during its evolution and that these decisions are socio-technical in nature and are based on uncertain, incomplete, evolving and conflicting information. The goal is lay the foundation needed to develop a system that can truly support engineering decision-making.

Keywords: decision-making, design process

INTRODUCTION
As design theory matures, it is becoming more decision-centric supporting the definition of design as the evolution of information punctuated by decisions. Current methods to support design decision-making are not sufficient in their ability to help teams make the best possible decisions. This turns out to be as much a cognitive psychology issue as it is an engineering problem. Understanding engineering design, human cognition and team decision-making can lead to tools to better support the new reality. The paper ends with a list of needs for design decision support systems.

DESIGN THINKING MATURITY
I was trained as a mechanical engineer. I know how to model systems, take data and develop an understanding for physical things. Most (nearly all) technical university courses are about how to model and analyze things. In my case these were physical things, but my education could have been in any engineering discipline, in business or in the sciences, and the courses still would have been primarily "thing" focused.

In the 1980s I was teaching mechanical engineering design at a university and began to appreciate that things come into being through process. During this time my thinking matured from being "thing" focused to being "process" focused. Process thinking was not new to some fields. In fact, in engineering there are control processes, chemical processes, fluid thermal processes etc. But these are nothing but process-things. What I became interested in was the process of developing these things. This type of thinking was led, at least from my US vantage point, by European thinkers and first made available to me in the book Engineering Design, by Pahl and Beitz [1]

In 1990, I began work on a US text book for mechanical engineers so that they could study the process of how things evolve from need to a final, working object. I agonized over the title as the term "process" was not really a part of the engineering lexicon except for describing process-things. I finally chose the title "The Mechanical Design Process" and the book was published in 1992. This title turned out to be a good choice and "process" is now generally used to describe product maturation. The 4th edition of the book was published in January 2009 [2].

When I began to research the design process in about 1984, my goal was to understand how objects evolve with eye toward developing methods and tools to better support this evolution. I don't mean CAD and solid modeling tools as these are representation tools for what is being designed, not tools that actually support the design process. In fact, I have argued in a paper I wrote in 1990 that CAD can be detrimental to the design process [3]. My arguments in this paper were that CAD was too slow relative to our cognitive speed, it forced thinking about form rather than function, and it could not support abstraction very well and other mismatches with conceptualization. Since writing this paper, CAD has evolved into solid modeling which is much better, but the arguments in the paper still hold.

During my research I was especially interested in developing a tool that could record the evolution and rationale for product evolution. This design rationale or design history system would be able to capture how a product came into being and could be reused, queried and vetted to form a permanent record of its birth, life and death. When I began, I focused on the evolution of the assemblies, parts, and features. I quickly realized that this wouldn't work because these things evolve during the design process and thus, focusing on them missed all the birthing – all the interesting, creative engineering.

My thinking turned to capturing the process through which things evolved. Process thinking encapsulates "thing" thinking as the process is about the evolving things. This shift in my thinking coincided with the text book mentioned above. However, it became evident by the mid 90s that process thinking, although much better than "thing" thinking, was not the best way to develop a design rationale system. What became evident was that *decisions are the punctuation marks in processes* and that my approach had to make yet another shift, one to decision thinking.

Thus, by the late 1990s my thinking had matured from thing, to process, to the decisions made during the process to develop things. Specifically, I wanted to understand and support the decision-making process. My research showed that on macro level, decisions were made at gates (in a stage-gate process) a countably few times during the evolution of a product. On the micro level – the cognitive level - they occur at about 1 decision per minute [4][1]. Somewhere between these extremes there is much need for decision making support.

Before we go on, a definition of decision thinking - decision thinking is focusing on the decision-making process used during technical or business development. "Focusing" implies understanding and supporting individual decision makers and teams of people making decisions when information is uncertain, incomplete, evolving and conflicting so that the decisions are robust.

I am not alone in this evolution in thinking. When I chose the title "The Mechanical Design Process", the word "process" was problematic as it was not commonly used in industry. Now, the product development industry makes good use of process thinking. When I started talking about decision thinking in the late 1990s few in industry knew what I was talking about. Now there is much anecdotal evidence that companies and the government are beginning to realize the importance of decision-making in their processes. My evidence for this is not firm, but many of my contacts seem to understand what I am talking about and few did five years ago, and the number of hits on the Robust Decisions web site continues to climb. Industrial thinking is maturing through "process thinking" to the decisions made during the process.

Also, during the 1990s the CAD industry matured into PLM (Product Lifecycle Management. Where CAD and solid modeling is about things, PLM is about processes that manage things and the documents about things. I have tried to interest the PLM vendors in decision thinking for about eight years. Initially they told me there was no customer pull (see the previous paragraph). Recently, I have gotten their attention. Now that they have the process under control, they too are maturing toward decision thinking.

DESIGN DECISION SUPPORT

There are thousands of decisions made in every design project. Many are made by individuals, others made by teams or committees. In any case, few are supported by formal methods or tools. This leads to one of two conclusions: Either there is no need for decision support (designers and design teams do very well without aid), or tools and methods have not yet been developed that give adequate decision support for the wide range of problems faced. Observation and limited results of formal studies lead to the conclusion that individual designers and, more importantly, teams of designers take too long to make decisions, frequently rehashing previous information, drop issues and fail to document rationale for later use. Thus, there is a need to explore why current decision support systems are not more frequently used by designers.

Most textbooks and Six-Sigma methods suggest use of the Decision Matrix and Pugh's method [2]. They are simple to use and have proven effective for comparing alternative concepts. The basic forms for the method are shown in Figure 1– the decision matrix on the left and Pugh's modification

[1] Research by Stauffer and Ullman showed that during the mechanical design process, designers broke problems into smaller and smaller chunks. In fact, this partitioning results in cognitive episodes that are about one minute long.. Similar results have been found from other types of problem solving.

on the right. In essence, the method, regardless of form, provides a means of scoring each alternative concept in its ability to meet a set of criteria. Comparison of the scores developed then gives insight to the best alternatives and useful information for making decisions.

		Wt.	Alternatives		
			Vendor 1	Vendor 3	Vendor 4
Criteria	Cost	.3	4	4	4
	Response time	.17	3	3	5
	Training time	.17	2	4	5
	Ease of use	.17	1	4	4
	Strong team	.1	3	4	2
	Team experience	.1	3		
	Total	1.0	16		
	Weighted total		2.8		

		Wt.	Alternatives		
			Vendor 1	Vendor 3	Vendor 4
Criteria	Cost	.3		+	S
	Response time	.17		+	+
	Training time	.17		-	S
	Ease of use	.17		+	+
	Strong team	.1		-	-
	Team experience	.1		S	-
	Pluses			3	2
	Minuses			2	2
	Sum			+1	0
	Weighted Sum			+.37	+.14

Figure 1 The Two forms of a Decision Matrix

The decision-matrix method is an iterative evaluation method that tests the understanding of criteria, rapidly identifies the strongest alternatives, and helps foster new alternatives. This method is most effective if each member of the team performs it independently and the individual results are then compared (not averaged - more on this later). The results of the comparison lead to a repetition of the technique, with the iteration continuing until the team is satisfied with the results.

The decision matrix/Pugh's method works quite well and can be done on a spreadsheet. Its strengths are:

- It forces itemization and articulation of the criteria. This provides a forum for team members to insure they evaluate using the same basis.
- It forces consideration of all the alternatives relative to a consistent set of measures.
- It provides a way to include the relative importance of the criteria, a viewpoint to weight the evaluation results
- It provides a way to combine the evaluations into a single satisfaction score, helping visualize the relative value of each alternative.
- It is flexible. Adding or deleting alternatives or criteria is not difficult.
- It gives some, limited guidance about what to do next to reach a decision

Limitations of the decision matrix are:

- Many decisions do not need this level of support.
- Can't include uncertainty – you must abstract all alternatives to the same level of abstraction. This limitation is not consistent with the Six Sigma philosophy of managing uncertainty and variation.
- Can't manage incomplete information – you have to evaluate against all the criteria regardless of whether or not you know anything about it.
- Difficult to mix qualitative and quantitative evaluation results. Where some of the features may be evaluated qualitatively and others the result of simulations and analysis, there is no way to fuse these results and all must be reduced to qualitative evaluations.

- Can't fuse different team member's evaluations
- It is assumed that all criteria can be traded off. There is no way to manage critical criteria (discriminating criteria that can not be traded off) as satisfaction is either a sum or weighted sum. This will be further addressed in Chapter 9.
- The underlying mathematics is not well supported by any theory or analytical methodology.

In summary, the decision matrix is very powerful, but limited. Efforts to resolve these weaknesses resulted in the Accord[2] software introduced in 2002. This software is based on Bayesian mathematics (a firm underlying mathematics); it has the ability to support uncertainty, to fuse team evaluations, and to combine qualitative and quantitative assessments. Nonetheless it has been very difficult to get wide acceptance for this product. So, the remainder of this paper will explore the decision-making weaknesses in an effort to develop a new set of requirements for the next-generation of engineering design decision support tool.

A COGNITIVE PSYCHOLOGY VIEW OF DECISION-MAKING

Research into how people make decisions is generally broken into two classifications: compensatory and non-compensatory [14]. Compensatory methods revolve around the trade-off of multiple attributes, where success with one attribute can compensate for lack of success in meeting another attribute. Typical of compensatory systems are the decision matrix, Pugh's method, and Accord. In engineering, compensatory methods are referred to as trade studies or trade-off studies.

Non-compensatory methods consider one attribute at a time and include no trade-off. There are many non-compensatory models that have been studied [7]. The simplest is called the lexicographic strategy. In this method all the alternatives are compared to the most important attribute. The alternative with the best value on the most important attribute is selected. If there is a tie, the next most important attribute is considered (hence the name of the strategy, since lexicographically is the act of writing a dictionary in this method starts with the first attribute than most of the second, and so forth much like a dictionary. For example, if you wanted to select the best fastener for a joint you might consider bolts, rivets, and adhesives. If the most important attribute is the ability to disassemble the joint, then bolts are the obvious choice and you are finished. But, if the most important attribute is a smooth surface then rivets and adhesives both meet this attribute and so the second most important attribute must now be considered.

Many similar strategies have been developed to explain behavior in decision-making situations. These range from the simplistic lexicographic, to full compensatory strategies. Studies have tried to determine which strategy is followed as people make decisions [7, 8]. In these studies individual decision makers have been simulated using various strategies and comparing the choices made to a "correct" answer. Key findings from these studies are:

- People use a variety of strategies, contingent on task and context factors
- Given that people have limited cognitive abilities, strategy selection is a compromise between accuracy and desire to minimize cognitive effort.
- People use decision strategies adaptively
- People are opportunistic changing strategies on the fly
- Failures in adaptivity occur
- The design of information environments, the practice of decision analysis, the design of man-model decision systems, and the measurement of values can be enhanced by considering the above.

These results provide direct implications about the types of support tools that may be useful in engineering design. They will be revisited to do just that in the concluding section. Before that, however, beyond the strategy followed, all decisions are based on estimates and our ability to make estimates is somewhat problematic.

[2] There is extensive discussion about accord in [5] and on the website, www.robustdecisions.com A free version can be downloaded for evaluation and free academic version are available from the author..

ESTIMATION, THE ROOT OF DECISIONS

Where past performance may be known, the present is obscured by its immediacy and the future is a best guess. In other words, very little is known with certainty, everything else is an uncertain estimate. The robustness of any decision and the risk incurred in making it can only be as good as the estimates upon which it is based. Some examples will help set the stage to examine estimation in detail, as well as the uncertainty that makes it difficult

For the first example, let's say that you are in the market for a new car. You're considering several, and have test driven a couple of them. You have just found out about a new model that will be introduced next year. You saw a fuzzy photo of this concept car in the newspaper, along with an article containing a vague description of its performance and an implication that it will be in your price range.

Suppose your main criteria for a new car are: initial cost, quality, mileage, and visual appeal. Your immediate decision is whether to add this car to your list of alternatives, realizing that it won't be available for a while (availability is another criteria that may be important to you).

Obviously, there is high uncertainty in your estimates of all the important criteria. For example, the car appears to be in a class that gets in the range of 25 to 28 miles per gallon (mpg) (11- 12 km/L), but the article said that, due to some new technologies, this car will do better. Based on the information you currently have, let's say that your best guess is that it will get 30 mpg. It may do as well as 35 mpg or as poorly as 27 mpg. These three values 30, 35, and 27, shown in Figure 2 indicate your uncertainty about mileage.

The manufacturer of another car you are considering lists its mileage at 27 mpg on its Web site. But your estimate of the mileage based on this information may still be uncertain; you may not trust manufacturer's numbers. You may conclude that your best estimate is 27 mpg, that it certainly won't be any better, and that, based on your knowledge about this manufacturer, it may be as low as 24 mpg.

Say that an independent consumer's group has tested a third car on your list, and that your buddy owns one. All data from these sources point to a mileage of 29 mpg ± 1 mpg. .

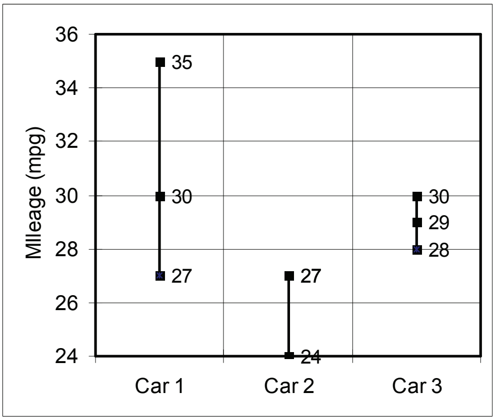

Figure 2. Uncertain mileage of cars

There are three key points to consider in this example:

1. High uncertainty can be caused by *lack of knowledge,* as is the case with Car 1. While the uncertainty might easily be reduced by speaking to experts or reading reports, sometimes it can only be reduced by research and extensive effort, and sometimes it can't be reduced at all.
2. When something is well known and understood, as with Car 3, the uncertainty will be in the *variation* between individual cars.
3. Often, as is the case with Car 2, you have *a mix of lack of knowledge and variation.*

Before you write this example off as too simplistic, or not representative of the kinds of information on which you base decisions, itemize a couple of important factors you used in a recent real-life decision and note the most likely estimate—the best you could expect, and the worst. Then note whether the uncertainty you faced was due to lack of knowledge or just the natural variation among things.

Another example demonstrates the difficulty in estimating the time it takes to do an easy task that you have not done before. I once did a simple experiment, using the questionnaire shown in Figure 3 in which I asked people to estimate how long it would take to clean up a stack of dishes.

Before you read on, I suggest you make your own estimate about cleaning the dirty dishes. Then, to put it in perspective, reflect on the complexity of this task relative to other tasks you are involved in.

ROBUST DECISIONS

A SIMPLE ESTIMATION PROBLEM

You have just had a dinner party and the stir-fry, salad, fresh bread, apple pie and coffee were all great. Your guests have gone and it is time to clean up. Your dishwasher is broken and you need to hand-wash the dishes, silver, and pans listed below; and put them in the drying rack next to the sink. The dishes have been sitting randomly stacked in the sink and on the counter for a couple of hours, but no food is burned on.

You need to clean:

- 4 large dinner plates
- 4 desert plates
- 4 sets of silver (2 forks, knife and spoon)
- 4 sets of coffee cups and saucers
- 4 salad bowls
- 2 serving bowls
- Salad tongs
- Bread knife
- Pie serving knife
- 1 wok
- 1 sauce pan
- A pie pan
- A bread pan
- A cream pitcher
- Serving spoon

You have a sponge, scrub brush, dish washing soap and plenty of hot and cold water. After stacking the clean dishes in the drying rack, you need to make sure the 40 in (100cm) square counter top and sink are clean also.

Estimate how many minutes will it take you to clean up the kitchen? _______

How many times have you hand-washed dishes in the last 100 days? ______

Thank you for your estimates.

Name: ____________________________ Organization: ________________________

Email: ____________________________ Phone: ____________________________

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Figure 3 Sample questionnaire

I have given this estimation exercise to thousands of people. For one group of fifty the results ware estimated by a normal distribution curve as shown in Figure 4. The mean estimate of this distribution is 32 minutes and the standard deviation is 10 minutes. These results bring up many questions. First, if you made your own estimate as I suggested, where does it fall on this distribution curve? Whose estimate is "right"? Is the 32-minute estimate any better or worse than yours? How long will it actually take someone to do these dishes?

One aspect of this exercise should be troubling to you. Washing dishes is a simple task that has been done many times. In fact, in my experiment, 60 percent of the respondents said they had hand washed dishes more than twenty times in the preceding 100 days. Yet there was a wide variation in the time estimates among respondents. How does that make you feel about estimates for more complex tasks? With this experiment in mind, how confident do you think you'll feel next time a colleague or a vendor says, "It will take about two weeks?" What does such an estimate mean? And if you asked another person who gave you a different value, what could you say about these two values? It gets even worse.

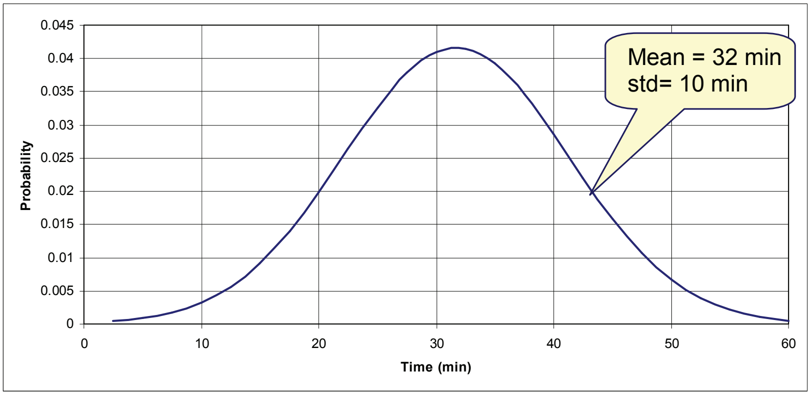


Figure 4 Results for base group

Rather than asking respondents to "estimate how many minutes it will take you to clean up the kitchen" as before, I asked a new group of people to "estimate how many minutes so that you are 50 percent sure you will be finished cleaning up the kitchen." The results were a mean of 18 minutes with a standard deviation of 6 minutes. I asked a third group, "Estimate how many minutes so that you are 90 percent sure you will be finished cleaning up the kitchen" Their results averaged at 29 minutes with a standard deviation of 8 min. Note that is implies that the first group was assuming about 90% confidence, but this was unstated in the original question.

Things get even worse if I anchor the problem. Anchoring sets a biased context for estimation. Anchoring occurs, for example, when a manager asks for an estimate via a question or statement that includes a predetermined amount: "I don't see how we could commit more than $10,000 to this." $10,000 now becomes the anchor point. This stated amount biases all the following estimates that are generated. Anchoring can happen in subtle ways. Let's say you are bidding on a project and you have been led to believe that the customer has a ceiling of, say, $10,000. You are now anchored to this value and will try to force your project to fit it.

To demonstrate anchoring, I modified the dishwashing experiment again. I asked a group of subjects to estimate how long it would take to clean the dishes as before, but this time with the addition of "Your partner has told you that the kitchen needs to be clean in 15 minutes." This anchoring resulted in a new distribution with a mean of 17 minutes and a standard deviation of 5 min

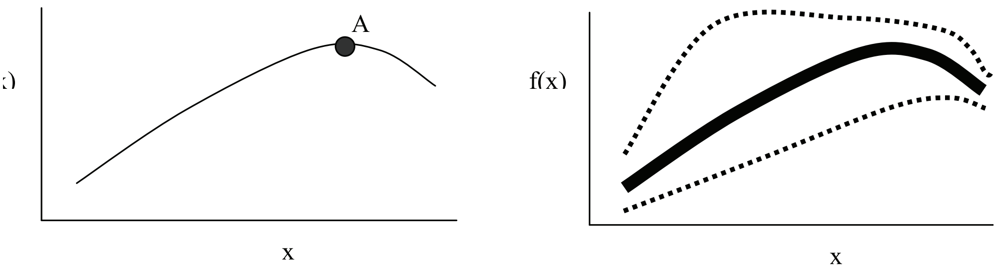
One conclusion to be drawn from these examples is that design decisions are based on uncertain estimates. The concept of uncertainty has begun to receive extensive attention [9, 8]. The importance of uncertainty was well captured by Richard Feynman when he stated: "If you thought that science was certain—well that is just an error on your part." A central premise of this paper is that the information upon which most decisions are based is uncertain; there is uncertainty in everything. So, let's explore uncertainty.

UNCERTAINTY IN DECISION MAKING

Decisions are easy to make if you have all the information and everybody involved agrees about what is important and how to interpret the information. Good decisions are more difficult because much of the information on which they are based is uncertain. Hugh Courtney, in *20/20 Foresight* [6] observed, "With rapid change comes uncertainty. And with uncertainty comes risk – and great opportunities." Some uncertainties you can control others you can not. Those you can control can be eliminated, or at least reduced, with the expenditure of time, money and people. Part of the decision making process is deciding when reducing them is worth it and when it is not.

Here we will define "**uncertainty" as any doubt, variation, change, or inconsistency in information**. The information in question can be of any kind—written, drawn, verbal, or even knowledge that is implicit and not articulated.

One topic I have avoided talking about so far is traditional engineering optimization. Consider a problem represented by a simple function, f(x) of a single variable, x. The goal is to find the value of x that gives the largest f(x). The situation may look as sketched in Figure 5a. Clearly, for this simple problem, the best decision is to choose .point A. Problems can seldom be modeled in this manner. First, for many problems, the functional curve is generally unknown and unknowable. Second, even if a functional relationship is known, it often has limited fidelity. Third, there is uncertainty in all the forums discussed above. Fourth, the alternatives are often discrete. And finally, some of the information may be qualitative rather than quantitative.



re 5 a) Simple optimization, b) with uncertainty

A more realistic view of this function, complete with uncertainty shown in Figure 5b. Now it is not so clear which is the best value if asked to choose. This is more representative of reality as it is only for very mature, well-funded, and well studied technologies that functions are sufficiently well-known with good fidelity and knowledge to keep the uncertainties small enough that optimization results have good meaning. .

In general, information uncertainty has three main sources, human cognition, the environment, and variation. The mental or cognitive information that people bring to each decision is uncertain. This uncertainty is caused by five factors. The first three apply to both individuals making decisions and to teams. The last two apply only to teams.

- **Knowledge limitations**: The more knowledge you have, the higher the certainty in your estimates—sometimes. (Sometimes more knowledge opens your eyes to uncertainty you were not even aware of.) The less knowledge you have, the higher your uncertainty, always. Sometimes this form of uncertainty is called "ambiguity" or "epistemic uncertainty" (*episteme* is Greek for knowledge). If you try to determine the cost of a car from a description in the newspaper, you can only guess; this is highly uncertain. You can gain more knowledge by looking up the price at the manufacturer's web site. This will give you a better idea, but there is still some uncertainty. When the car is available, you can go to a dealer and further refine the price, but until a contract is signed there is still a level of uncertainty about the price. In general, you can only reduce knowledge uncertainty by more modeling, additional expertise, or other forms of learning. All of these courses of action require time and other resources. As engineers, we continuously ask: "When is it worthwhile to expend additional resources to improve the certainty of knowledge?"
- **Approximations**: Approximation uncertainty arises because mental, analytical, and physical models are only simplified versions of the real world. Often the level of approximation of an analytical model is referred to as its **fidelity**. Fidelity is a measure of how well a model or simulation analysis represents the state and behavior of a real-world object.

Back-of-the-envelope calculations are low fidelity, whereas detailed simulations—hopefully—have high fidelity. Experts often run simulations to predict performance and cost. At the early stages of their projects these simulations are usually at low levels of fidelity, and some may be qualitative. Increasing fidelity requires increased refinement and increased project costs. Increased knowledge generally comes with increased fidelity, but not necessarily; it is possible to use a high-fidelity simulation to model "garbage" and thus do nothing to reduce uncertainty.

- **Viewpoint differences:** People's estimation of any situation is colored by their viewpoint, the organization, and the field they represent: The marketing manager thinks that look and feel is most important, the engineer thinks its functionality, and the CFO is sure it's cost. None is right and all are right, and this results in an uncertain picture of what is important. There are ways to make use of viewpoint differences to strengthen buy-in, which I will describe later in the book.
- **Terminology imprecision**: Imprecision arises when inexact terms are used to describe things when communicating about a project. Since each discipline may use different jargon, it is often a challenge to find out, for example, that one person's net cost is another's gross cost.
- **Disagreement among team members**: Team members' interpretations of the available information may be different or **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 neither good nor bad; they are just different interpretations of the available information. Conflicting interpretation is different from conflicting viewpoint, and must be handled differently.

The second source of uncertainty is the organization itself.

- **Other projects:** Dependence on other projects or tasks adds uncertainty because of the availability, certainty, and quality of information derived from them.
- **Organization priorities and policies:** Organizations create uncertainty both through their procedures and their instability. We have all been on projects that were cancelled or radically altered by an organization. Although it may seem difficult to insulate a project from organizational changes, well-defined projects that are making good progress—are on schedule, within cost, and headed toward their expected features and functions—are least likely to be cancelled, changed, or otherwise tinkered with.

The third source of uncertainty is variation. Variation occurs in all information, even if the level of knowledge is high and the organization is stable. Variation has four causes.

- **Statistical** (i.e., stochastic uncertainty)**:** Statistical variation is the result of the fact that all things behave in random ways. The weather will change, material properties are not constant, even the time it takes to tie your shoes will vary. In manufacturing, the term "variation" is the actual fluctuation in measured process output as the process is repeated. In projects that have not occurred before, the **variation is the *anticipated* fluctuation in measured process output as the process is repeated**. In the dish washing example earlier in this chapter, the anticipated variation is given by the standard deviation.
- **Aging**: Often duration, cost, performance, or another property will vary with time. For mechanical products made of plastics, for example, strength will usually degrade. For business processes, the time an activity takes may shorten with time
- **Environment**: Environmental effects can cause properties to vary. These may be changes in temperature, wind, the organization in which the decision is made (as discussed above), which engineer you get on the project, who is sick this week, etc.
- **Measurement errors**: Statistical variation arises from random error in measurements of a given quantity.

Beyond the fact that most estimates are poor, our ability to estimate probabilities is even poorer. For many years psychology researchers have shown that, when asked to estimate the probability of some event, people do a very poor job. In, *Reckoning with Risk* [8], Gerd Gigerenzer, found

1. Most physicians (indeed most people) confuse the probability of a test detecting a disease (its sensitivity) with the probability of actually having a disease given the test being positive.
2. People assume a reference class when they try to understand a single event probability.
    a. When asked to judge "the probability of X", estimates are about 50% higher than when asked to estimate "how many out of 100 would do X". Probability judgments are about 50% than frequency judgments. Not clear the reference class for probability. RC clear for frequency structure.
3. Many probability estimates are too imprecise to be expressed by numbers. Experts can give reliably give judgment about order but not magnitude
4. Judgments are influenced by category scale. Given two different scales to make an estimate will give two different results. If you asked people to guess how many jelly beans in a jar of 100 bean and gave one a scale from 50 – 150 and the other a scale for 90 -190, you would get different estimates.

TEAMS

Teams don't make decisions, or do they? It depends on whether you consider a decision as an event or a process. If it is the event of signing off on a purchase order, a design drawing or other artifact that commits resources; then a decision is made by one person. But, if you consider decision-making more than an event, but rather the process combining the knowledge and expertise of many people to frame the problem, evaluate the alternatives, fuse the results and decide what to do next; then most decisions are made by teams.

Most cognitive psychology research focuses on individual decision makers. There is very little research on teams in which some of the people know some of the information and no one person knows all the information – the typical situation in engineering design [14].

There are many good books on teams. Probably the best is *The Team Handbook* [10] which has sold over 1.3 million copies since its introduction. Although a team's main product is the decisions it makes, the decision-making process is only covered on 10 out 301 pages in the *Handbook*. *The Team Handbook,* lists "Ten Ingredients of a Successful Team" as:

1. clarity in team goals
2. clearly defined roles
3. clear communication
4. well-defined decision process
5. beneficial team behaviors
6. balanced participation
7. awareness of group process
8. established ground rules
9. an improvement plan
10. use of scientific process

A successful team needs these "ingredients". A well-defined decision process - Ingredient #4 in the list above - can supply virtually all the other ingredients.

In the book, Making Robust Decisions [5], I tried to capture all of the important team concerns in a single diagram reprinted as Figure 6. Each of the topics in the figure contributes to team decision-making success. It is hypothesized that tools can be developed that support all of these topics.

Most current tools support teams by supporting individuals and then averaging the results. This usually averages out all of the interesting information (like mixing paint and always getting brown) and violates Arrow's Theorem. Say that there are three team members, one who orders the options A > B > C, another who evaluates B > C > A, and a third who says C > A >B. All three voters have rationally ordered preferences, but on the average (in two out of three cases), they prefer A to B, and prefer B to C, and also C to A. The resulting social order is not rational, and provides no basis on which to make a decision [13].

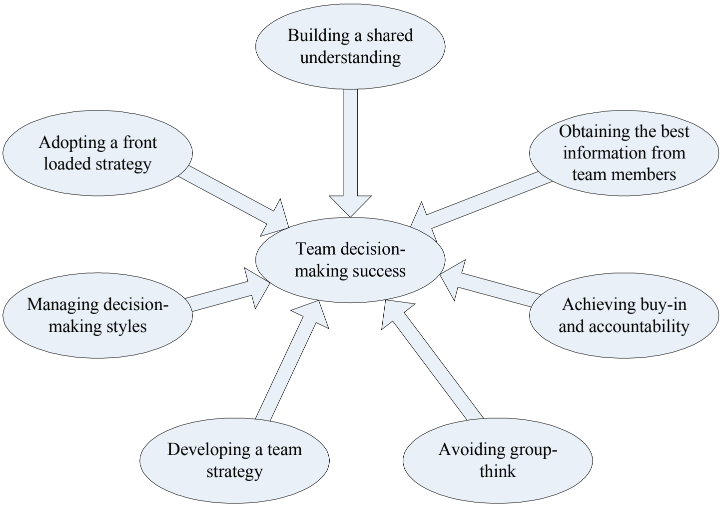


Figure 6 Elements for decision team success

CONCLUSIONS

In this paper I have tried to lay the foundation needed to develop a system that can truly support engineering decision-making. Even after nearly 10 years of trying to develop such systems. I remain convinced that it is possible to develop a system that can support the engineering decision-making process. I am not alone in this belief. Payne et al [7] state: "One way we can encourage decision makers to be more normative (more precisely reflect their values and beliefs) is by reducing the cognitive effort demands of the task." Further, Bell, Raffia Tversky [11] suggest; "Rather than abandoning decision analysis, we should try to make it responsive to the complexities and limitations of the human mind."

In a 1995 paper [15] I developed a taxonomy of design problems in order to better understand tools needed. In this paper, I have taken a different approach to the same end. In an article by Henry Ford in 1906, he spelled out what was needed for a practical car for the American public and then proceeded to design, build and market the Model T [12]. In the same vein I suggest that tools are needed that:

- Provide an adaptive environment that spans from non-compensatory support to full normative, compensatory methods and can change as needs change.
- Require no additional cognitive load on the decision makers.
- Supports distributed engineering team decision-making
- Support uncertainty in all its forms and capture it in a form that is easy to capture and as accurate as possible.
- Capture the decision making history for reuse and review
- Supports a mix of information fidelity, form qualitative to quantitative.

I hope that my work over the past few years is moving in this direction. Time will tell.

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