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Experimentation and its Role in Engineering Design: Linking a Student Design Exercise to New Results from Cognitive Psychology*

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This paper advances the hypothesis that engineering design is most effective when heuristics are used in many aspects of the design process, particularly in structuring sequences of experiments and adapting the design based on data. These heuristics appear to be natural behavior in the sense that engineers will use them when no training or external incentives are offered to encourage alternative approaches. Our observations of seven repetitions of a student design exercise with a total of over 300 students are consistent with our hypothesis. The approaches used by students appear to be economical and highly effective even though they are not consistent with theoretically optimal experimentation techniques. Our observations are related to recent research in cognitive psychology, especially the work of the Adaptive Behavior and Cognition group regarding 'fast and frugal heuristics' and also the observations of some researchers in Design of Experiments. The implications for design practice and education are considered.

Keywords: heuristics; disciplined design; design education.

I. MOTIVATION

A HEURISTIC is a generally reliable, but potentially fallible, simplification that enables a problem to be addressed within resource constraints. Given that engineering design poses many very difficult problems and that it must be conducted under stringent competitive conditions, it seems natural that heuristics would be a major part of the professional practice of engineering design. An ad hoc approach is one that is suited to a specific purpose and cannot be guaranteed for general purposes. Given that engineering poses a broad range of distinct challenges with different problem structures, it is natural that different heuristics are applied to different problems. So, the terms 'heuristic' and 'ad hoc' denote what appear to be reasonable strategies for tackling engineering challenges.

Nevertheless, in engineering design, there is a strong tendency to believe that general-purpose approaches described as 'systematic' and 'mathematically rigorous' are to be preferred to 'heuristic' or 'ad hoc' approaches. For example, the United States National Science Foundation states that in pursuing research they seek 'rigorous application of fundamental theories taken from disparate disciplines, such as mathematics, economics and operations research, to the engineering design process' and that 'preference is given to approaches that include mathematical rigor, as opposed to *ad hoc* and heuristic methods that have limited application' [1]. This preference does not appear to be limited to academic circles. A recent trend toward more systematic engineering processes is the proliferation of Six Sigma programs, which are described as 'analytical' [2] or 'highly disciplined' [3]. Thus it appears that both academia and industry overtly prefer general-purpose problem solving as opposed to heuristics.

The motivation of this paper is to build a positive case for heuristic approaches to engineering design and to argue against the idea that making designers use a more systematic, rigorous, general-purpose approach leads to better designs. This paper was inspired by the authors' experience leading a design exercise intended to teach students about experimentation and its role in engineering. The students resist using a general-purpose approach and those teams that tended to be more systematic did not fare better in the exercise. Our observations paralleled our experiences in industrial settings with experienced engineers. These observations have led us to relate recent cognitive science research to engineering design. In doing this, we follow many others who have linked design research with cognitive science [4–8]. It is hoped this paper will lead to careful scientific

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investigation of the nature of heuristics applied during design and the ways these heuristics provide value to the outcome of that process.

The education module

The educational module is designed to teach undergraduates about experimentation in engineering design. The module has been part of the Undergraduate Practice Opportunity Program (UPOP) program at MIT for four years. The name UPOP was chosen because it complements the very successful Undergraduate Research Opportunity Program (UROP). What UROP has done for research experiences, UPOP aims to do for engineering practice experiences. UPOP includes an industrial summer intern experience coupled with pre- and post-intern activities designed to create an integrated program whose goal is to provide students with the opportunities to apply their classroom learning in stimulating, real-world settings [9]. A major part of the pre-intern learning occurs in a one-week course structured like an executive education or corporate training seminar. The students do all modules as ten-person teams and each team has an experienced engineer who acts as a mentor to the group.

The co-authors have jointly developed a three-hour module on experimentation in design and delivered it to the groups over the four years of the UPOP program. More than 300 students have participated in the module so far. The module begins with a short lecture on experimentation and its role in design. The themes for the lecture include variability, quality, design of experiments, and Taguchi methods. Specific concepts and tools introduced include balance, orthogonality, statistical efficiency, and deliberate introduction of noise factors into experiments.

After the lecture, the students engage in a brief design contest depicted schematically in Fig. 1 and employing the rules listed in Table 1. The students are asked to develop a paper airplane that will fly a given distance consistently. The design space is limited to a parameter space of four variables, each variable having three levels. There are thus 81 possible distinct paper airplane designs. The template used for folding the planes is based on 'Taguchi airplanes' developed by Eppinger [10]. The teams have a limited budget to explore the design space. A maximum of 30 flights can be made, so the search is necessarily incomplete. Further, there is competitive advantage to limiting the development cost by experimenting with even fewer alternatives. In addition, the development time is limited to 40 minutes. Once the allotted development time has elapsed, the teams submit

Table 1. The rules of the design challenge

Every team designs a paper airplane (constrained to the choices on the template).
The development budget is \$300. Any experimental flight costs \$10.
There are 40 minutes for all planning, experimentation, and decision-making.
The competition comprises five flights. A teaching assistant does the throwing. • \$100 for each landing in the 'target' (17 ft–22 ft) • \$50 if past the target (>22 ft) • \$0 if short of the target (<17 ft)
Profit equals revenue minus cost. The team with the highest profit wins the contest.

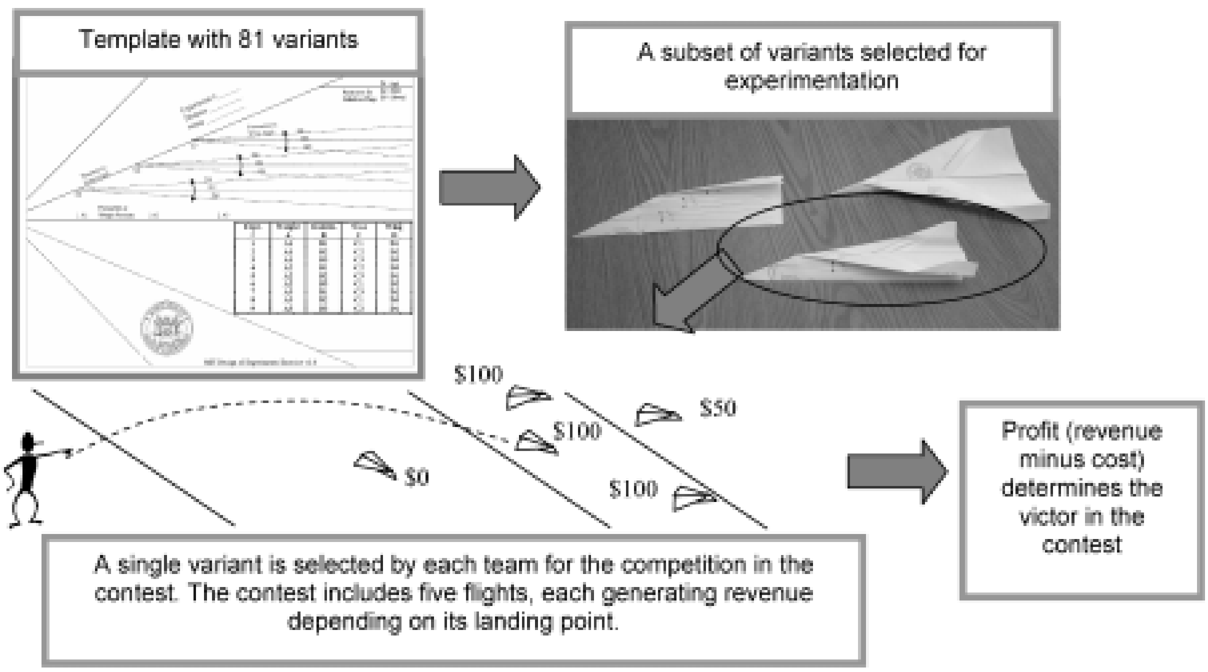

Fig. 1. A schematic representation of the design challenge.

their chosen designs and the planes are flown five times. The payoff for the flights is based on their flight distance. This payoff minus the development costs incurred represents net profit. The team with the highest profit wins the contest.

OBSERVATIONS OF THE DESIGN CONTEST: PROCESSES USED AND RESULTS OBTAINED

In delivering this module an interesting finding has emerged. Although the lecture describes factorial design of experiments and its advantages, student teams generally do not elect to use factorial design for the contest (note that the rules in Table 1 do not compel them to do so). When students engage in design, they naturally gravitate to a process that is more adaptive than statistical Design of Experiments (DOE) or Taguchi methods. They use their current knowledge about paper airplanes and engineering science to make a series of guesses interspersed with experiments to try to determine what will work best. They repeat this process until they are satisfied with their choice or until time runs out. This general approach has many variants, but students naturally tend to use an approach along these lines.

This heuristic, adaptive approach has been successful in competition with factorial DOE. The number of experiments conducted by student teams is generally quite low (3–7 typically) compared with that needed to perform a resolution III factorial design (nine experiments if all four factors and all three levels are included). The payoffs achieved by teams using the heuristic approach apparently exceed the average payoff provided by factorial design or the payoff through selecting the alternatives at random and selecting the best one. These conclusions were made by comparing the student team results to an investigation of factorial design and random selection using data re-sampled from a full factorial experiment with the paper airplanes [11]. On the one occasion a TA strongly mentored a team to use an orthogonal array, the team did so. However, in alignment with our other findings, this team did not attain the top-performing airplane, despite having high development costs.

Because this design activity was developed as an educational activity and *not* as a scientific experiment, we cannot draw conclusions about the statistical significance or scientific validity of the trends observed. The evidence so far is purely anecdotal and is presented here to motivate further exploration of our hypothesis. In this case, we observe that the approach that engineering students naturally tend to apply apparently leads to better designs and lower costs than theoretically superior experimental plans. In the next section, we consider related inferences about the design process and designers.

RELATED OBSERVATIONS FROM INDUSTRY AND ACADEMIA

The observations made during this design contest seem to us to be closely related to a number of other observations one can make about engineering design:

- Many companies are teaching engineers about statistical DOE and encouraging (or sometimes requiring) engineers to use DOE in product design. Despite this training and encouragement, engineers often strongly resist applying the techniques. Indeed, it is our experience that the best engineers are often the strongest opponents of such requirements.
- The resistance to systematic approaches is not limited to DOE. Design approaches that emphasize 'rational' or 'scientific' methodology [12, 13] have not been widely embraced by experienced and successful design engineers in industry or academia.
- The teaching of design is generally recognized as best done by hands-on, project-based courses [14]. Educators who are also excellent designers are among the strongest opponents of teaching a single, systematic process for design.
- The early examples of human accomplishments in design (e.g., Stone-age tools, Neolithic stitching, Bronze-age metallurgy) are a result of the natural human design process unaided by artificial, systematic methodology.
- Despite the continued lack of a single systematic design process in industry, highly successful results continue to accumulate as humans practice engineering design by the processes currently in use.

All of these observations suggest that humans are naturally skilled at design. It is possible that the natural, heuristic design process is superior to any systematic, general-purpose process that has been so far devised. Recent cognitive science findings lend some support to this hypothesis.

REVIEW OF SELECTED RECENT COGNITIVE SCIENCE FINDINGS

Recent cognitive science research indicates that problem solving behaviors of humans and animals in naturalistic tasks is often superior to theoretically optimum general-purpose problem solving methodology. In particular, Gigerenzer's Adaptive Behavior and Cognition (ABC) group has developed a persuasive set of results summarized in three recent books [15–17]. The ABC group builds upon Simon's concept of 'bounded rationality', which acknowledges the tight resource constraints imposed in real world tasks and their implications for problem solving and economic activity. The ABC group holds that some interpretations of bounded rationality have distorted the concept in such a way that it is practically and

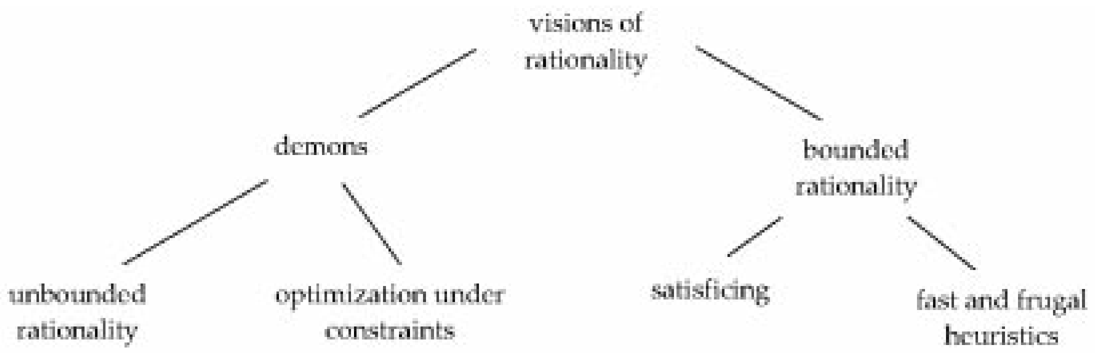

Fig. 2. Models of bounded rationality [19].

psychologically implausible. Figure 2 depicts a way of categorizing various ways of conceptualizing rationality. On the left side are approaches based on 'demons' that need not respect the computational or cognitive constraints. Under this category is 'unbounded rationality' in which a person is rational only if he acts to maximize utility despite the unrealistic computational demands this can imply. If 'unbounded rationality' is reformulated to include the resource constraints, a new problem is created that may be even more computationally demanding than the previous problem. Alternative conceptions of rationality that inherently respect resource constraints are presented on the right of Fig. 2. One example is Simon's concept of satisficing behavior in which stopping rules are used to simplify the problem. A new conception of rationality is 'fast and frugal heuristics.' As discussed in the next sub-section, the ABC group has shown that many heuristic strategies are extremely effective as long as they are applied in a manner consistent with the naturally occurring domains in which they evolved through natural selection or learning [18]. As a consequence, a new conception of rationality emerges in which bounded rationality is neither sub-optimal nor irrational.

SOME FAST AND FRUGAL HEURISTICS

The simplest heuristic explored by the ABC group is the 'recognition heuristic.' In many cases, if a person or animal faces a choice between two objects and recognizes one object and not the other, then they will assume the recognized object rates higher along some dimension. This heuristic is employed, for example, by rats that eat foods only if they have eaten them before or if they smell them on the breath of other rats. This heuristic has significant advantages for an animal that scavenges for food and faces the possibility of poisoning. The ABC group has shown that the recognition heuristic is effectively used by humans in other domains.

A second simple heuristic applies when one recognizes both objects and has to retrieve further information to make an inference. 'Take the Best' (TTB) is a lexicographic strategy for search and use of information [20, 21]. Attributes or cues about the two objects are ranked for their effectiveness in distinguishing relative to a desired characteristic. The attributes for the two objects are then compared in rank order with the first cue that differs between the compared objects being the basis for the decision. TTB employs a very simple stopping rule—use the highest ranked cue that has been successful for discrimination and ignore the rest.

Many tasks of interest go beyond simple comparison of two objects and involve choice among numerous alternatives. The fast and frugal character of 'Take the Best' can be preserved in cases of this type through the use of a simple stopping rule to limit information search: seek cues in rank order until enough is known to make a decision. The decision rule in this case is the 'elimination heuristic' in which successive cues are used to eliminate more and more alternatives until a single option remains. Eliminated options that do well on later criteria are not re-instated; indeed, they are not even evaluated on the later cues, they are ignored.

In a similar spirit, the 'QuickEst' heuristic [22] is designed to estimate the value of objects (relative to a defined criterion) while using as little information as possible. QuickEst associates a set of cues that are related to the defined criterion and these cues are characteristics of the kinds of objects being examined. For example, if city size is being estimated, whether it has a professional football team and whether it has a symphony are such cues. To estimate the criterion value of a given object, QuickEst looks through the cues in reverse order until it comes to the first one the object does not possess. It then estimates the object criterion as the mean value associated with the absence of that criteria. Thus, QuickEst uses features that are present to eliminate all smaller criterion categories and absent features to eliminate all larger criterion categories, so that only one criterion estimate remains. No cue combination is necessary, and no adjustment from further information is possible.

Another heuristic that uses the elimination principle is the 'Categorization by Elimination' heuristic [23]. In this case, the task considered is choice of a category—from among several possible—that a given object falls into. The simple heuristic makes category judgments by using each successive cue to eliminate some of the categories until only one category remains. Again no reconsideration of eliminated categories is allowed due to information from later cues.

In this rather brief overview, it is possible to see that the mechanisms proposed by the ABC group involve very little computation and information. This is why they are referred to as 'fast and frugal' heuristics. The next subsection considers how much accuracy is sacrificed to attain the speed and economy of these simple heuristics.

ACCURACY OF SOME FAST AND FRUGAL HEURISTICS

The most detailed assessment of the fall-off in accuracy with a fast and frugal heuristic has been done with the 'Take the Best' (TTB) heuristic [24, 25]. TTB has been compared with linear regression and with two Bayesian approaches including Bayesian Networks, which are considered by many to be the best mechanism for extracting useful information from data. Table 2 shows 20 cases that have been assembled and compared by Martignon [25]. In the fitting task, the entire data set is used to train the various methods. In the generalization task, 50% of the objects in the data set were chosen at random 10,000 times and the model obtained on the training set was then tested on the remaining 50%. It is remarkable how well the simple TTB heuristic does in this comparison, especially in the generalization task. It often is actually more accurate than linear regression (indeed for the overall average for the 20 data sets it is superior by 3% in generalization) and is amazingly competitive in most data sets with the Bayesian Network. Two explanations have been identified for the accuracy of TTB [26]: (1) the simplicity of TTB provides robustness as compared with linear regression, which tends to 'overfit' data; and (2) the TTB heuristic exploits the structure of the information in the environment (for example, the importance of dominant cues) in ways that general approaches do not.

Another heuristic whose accuracy has been studied by the ABC group is the recognition heuristic. For instance, a problem has been devised in which two city names are presented to a subject and the subject is asked to select the city with a larger population. A surprising result is that American students perform better given pairs of German cities than they do given pairs of American cities and German students perform better given pairs of American cities than they do given pairs of German cities.

The resolution of this paradox hinges on the recognition heuristic. It has been shown that subjects presented with one city that they recognize and one city that they do not, assume that they city they recognize is more populous. This strategy is quite successful if the subjects recognize about half of the city names in the set and works poorly if the subjects recognize the vast majority. Hence, more knowledge can be detrimental to successful performance. This 'less is more' effect is arises frequently in analysis of simple heuristics.

The ABC group has also analyzed the performance of QuickEst. This heuristic has been shown to be accurate for estimating quantities whose distribution is such that small values are common and large ones rare. Such distributions apply to a

Table 2. Performance of different algorithms in 20 data sets [24,25]

Environment			Fitting					Generalization			
	# Objects	# Cues	PM	TTB	Reg	NB	BN	TTB	Reg	NB	BN
Ozone in San Francisco	11	3	85	84	85	84	84	79	77	80	78
Cow manure	14	6	83	79	79	79	80	76	72	78	79
Oxidant	17	4	93	84	84	84	84	80	76	81	82
Mortality	20	15	100	77	83	78	79	62	54	66	67
House price	22	10	96	86	86	87	87	84	68	86	86
Rainfall	24	6	71	67	71	68	68	53	56	57	59
Biodiversity	26	6	88	84	80	83	83	80	72	80	82
Attractiveness of women	30	3	80	71	71	71	71	66	67	68	59
Attractiveness of men	32	3	75	73	73	73	73	71	69	72	70
Mammals' sleep	35	9	95	78	79	77	83	75	65	76	80
Car accidents	37	13	93	71	79	75	75	64	64	71	71
Obesity at age 18	46	10	70	74	74	77	79	71	63	71	69
Fuel consumption	48	6	87	78	79	78	80	73	74	76	76
Homelessness	50	6	82	69	70	68	77	63	62	64	65
Professors' salaries	51	5	87	80	83	80	84	80	80	80	81
High school drop out rates	57	18	90	65	72	65	65	60	54	61	60
Land rent	58	4	82	80	81	80	81	77	80	77	78
City population	83	9	80	74	74	74	76	72	71	72	74
Body fat	218	14	87	59	61	80	82	56	55	79	80
Fish fertility	395	3	75	73	75	73	75	73	75	74	75
Average over the 20 data sets			85	75	77	77	79	71	68	73	74

PM = profile memorization, TTB = take the best, reg = regression, NB = naïve Bayes, BN = Bayesian network.

wide variety of naturally occurring phenomena including a large class dominated by the 'rich get richer' model [27]. This growth pattern applies to cities so that very big cities are much less common than smaller ones and this permits QuickEst to estimate rapidly the small sizes of most cities. The performance of 'Categorization by Elimination' has been shown [28] to be within a few points of the accuracy of categorization algorithms that employ exemplar and neural nets despite only using one quarter of the information that these other models employ. In situations where categorization must be fast (for example, hospital emergency rooms) and where additional cues take time to search for, the fast and frugal, and surprisingly accurate, 'Categorization by Elimination' has striking advantages.

While this section has emphasized the research of the ABC group, other cognitive science research has also had important implications for use of heuristics. In the 'heuristics and biases' research program [29], human departures from rational prescriptions are identified and sometimes mitigated. Most of the research in the 'heuristics and biases' program has been conducted in academic laboratory environments, which are usually not very similar to real world problem environments. Recognizing this, Klein [30] has coined the term 'microcognition' to describe cognitive processes such as short-term and long-term memory, sensation, and attention, which tend to dominate in laboratory-based tasks. By contrast, the term 'macrocognition' describes skills needed to build and maintain the big picture, make sense of ambiguous data or large volumes of data, and maintain the same shared frame of reference with others. Studies have demonstrated that success in real world settings is predominantly determined by macrocognitive skills [31]. Macrocognitive skills may also be critical in engineering design and may have even dominated in the simple design exercise described in the 'Education module' section above,

We have now described a range of recent research results in cognitive psychology. These results are giving rise to a new conception of human rational behavior, 'ecological rationality,' in which behaviors are judged by their fit with the regularities of the natural environment rather than by traditional criteria such as self consistency or utility maximization [32]. We now explore the potential application of such concepts within engineering design starting with the role of experimentation in design.

HEURISTICS FOR EXPERIMENTATION IN ENGINEERING DESIGN

The cognitive science research just reviewed suggests that humans do not employ a general-purpose problem solving strategy, but rather choose from a toolbox of heuristics. The research also suggests that heuristics can be extremely effective when they exploit regularities of specific problem domains. Thus, adaptive application of heuristics is not only descriptive of natural behavior, but also prescriptive in the sense that the natural behaviors are as effective as any alternatives so far devised. This same model of human behavior and the same prescriptive conclusions may also apply to engineering design. This section explores this hypothesis in light of the design exercise described in 'The education module' section above.

The phenomena we observed about experimentation can be described as part of a spectrum of experimentation behavior as depicted in Fig. 3. At one vertex of the spectrum is prediction. If a designer knows all the technology and physics, experiments may be unnecessary or perhaps used only to confirm finally what is already established with a high degree of certainty. Another vertex is labeled 'Design of Experiments' in which specially devised plans are defined at the outset of the experiment for exploring the design space and gathering information efficiently in the presence of experimental error. Design of Experiments requires, in principle, very little a priori knowledge of the domain and, in some variants, leaves little room to adapt to data as it emerges. A third vertex is labeled 'build–test–fix', denoting a sequential

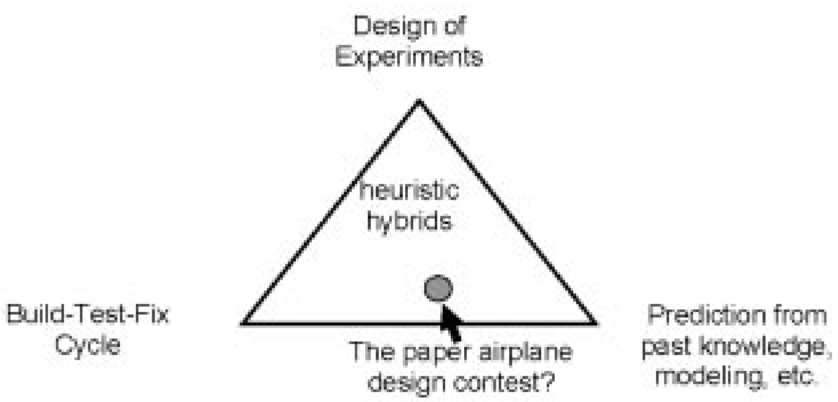

Fig. 3. Heuristics in experimentation.

adaptive approach guided by very little physical insight.

Our observations suggest that the paper airplane design contest was somewhat closer to the 'prediction' vertex than any other vertex. In the design exercise, we observed that student teams usually made conjectures based on physical intuitions before performing an experiment. For example, in beginning the process the team might decide that airplanes with larger wings are likely to glide farther than airplane with small wings. This informed an initial choice of design, which was then flown to establish an estimate of its performance.

Our observations also suggest that the paper airplane design contest was somewhat closer to the 'build–test–fix' vertex than the DOE vertex. For example, the teams frequently changed only one factor at a time, which is an approach strongly discouraged by DOE. A common scenario is that a team might observe that their current design lacks directional stability, and therefore tends to drift left or right, making flight distance less consistent. The team might then discuss the option of folding up the tabs on the wing tips as provided on the template. Some team members might mention that airplanes typically have vertical stabilizers on the tail of the plane and that such vertical stabilizers tend to keep a plane's nose pointed in the direction of flight. Since the tabs on the wing look like a conventional vertical stabilizer but are attached at the wing tip rather than the tail, the team might infer they serve to promote directional stability but also experience some uncertainty. As a consequence, a team might agree that the costs of an experimental flight are justified to explore this issue. The current design might then be modified by folding up the wing tips and a single trial or a few replicates might be conducted. This kind of process was repeatedly observed. As a result, many sequences of experiments conducted by the teams varied in only one parameter from trial to trial.

We speculate, based on observations in industry, that while engineering design behavior can be observed all over the spectrum, a large amount of engineering design is as far from the DOE vertex as was the behavior we observed in the student design contest (Fig. 3). Further, we suggest that that this strategy is well suited to most engineering practice providing better outcomes in many cases than other points on the spectrum. As support for this hypotheses, consider that the pattern of single factor experimentation observed in the student design project has long been observed in industrial experimentation. The noted statistician Cuthbert Daniel made the following observation based on extensive consulting experience:

> Some scientists do their experimental work in single steps. They hope to learn something from each run, or trial. They see and react to data more rapidly than experimental agronomists or clinical investigators whose endpoints may take months or years to materialize. The statistician who tells such an experimenter that he can secure much greater precision or validity by doing 16 or more runs in a balanced set, may be listened to with courtesy, but rarely with enthusiasm [33].

We propose that Cuthbert Daniel had observed a commonly used engineering heuristic—in experimentation, change only one factor at a time. Further, Daniel observed resistance to abandoning the heuristic in favor of prescriptions derived from mathematical theory. Statistical theory suggests that balanced sets of experiments will be more efficient. But practitioners often have a goal at odds with DOE—'to see and react to data more rapidly.' Daniel, rather than pushing the prescriptions of DOE overly hard, offered practitioners a further heuristic—use one factor at a time plans only when the 'effects are expected to be of magnitude 4σ or more' and when the experiments in question yield results quickly so that they 'cannot conceivably be used in agricultural field trials, in long term clinical trials, . . . or in studies of consumer product shelf life' [33]. Cuthbert Daniel seemed to understand that experimenters had an adaptive toolbox and that they needed simple rules to determine which heuristic to select. We propose that the kind of advice Daniel offered is among the most useful in promoting effective engineering practice and is well supported by recent cognitive science. As an interesting finding relative to the accuracy of this heuristic, recent work [34] has uncovered a finding much like those of the ABC group relative to the use of formal DOE processes. An adaptive variant of one-factor-at-a-time experimentation (adaptive OFAT) was compared to factorial designs in a study of 66 responses from published experiments. The result was that OFAT provided more improvement than factorial designs as long as experimental error was less than a quarter of the factor effects (as anticipated by Cuthbert Daniel). In addition it was found that adaptive OFAT provided more improvement when interactions among control factors are more than one quarter of all factor effects. Further work indicates that the effectiveness of the adaptive OFAT heuristic is strongly related to the general structure of statistical effects in engineered systems including effect scarcity, effect hierarchy, effect hereditary, and the predominance of symmetric two-factor interactions [35]. Thus, we have an existing case where 'ecological rationality' seems to be observed in engineering design—a heuristic has evolved, is used naturally by designers, and effectively exploits the structure of engineering problems to deliver better performance than theoretically optimal alternatives.

The tension between theory of DOE, prediction, and adaptation has been further explored by George Box, a pioneer and leader in statistical methods for engineering. Box argued that the mathematical basis of DOE has led to over-use of formally optimal experimental designs that tend to be 'one-shot' procedures [36]. Thus, Box argued against a push by the statistics community toward

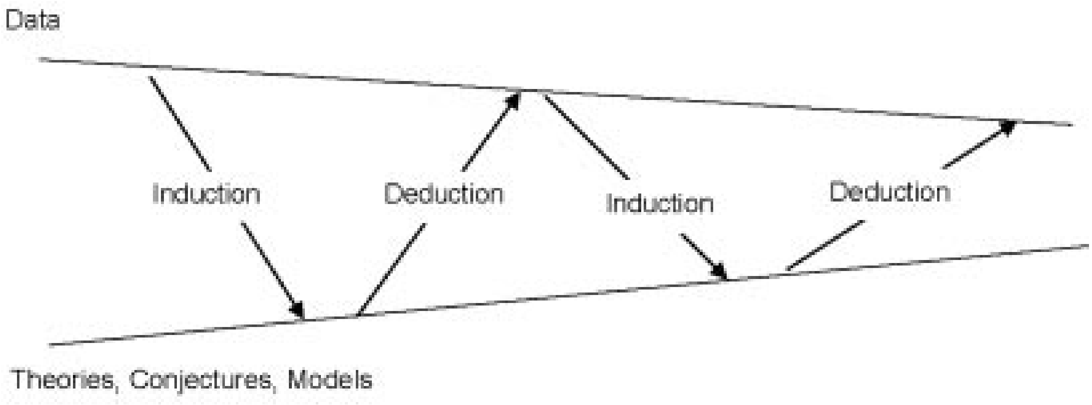

Fig. 4. A cognitive model of experimentation (adapted from [36]).

the upper vertex of Fig. 3. Instead Box advocated Response Surface Methodology (RSM)—an iterative and partly heuristic application of DOE for seeking improvement. Box argued that RSM would enable more leveraging of human scientific insight. He described the use of experiments as part of an iterative cycle as depicted in Fig. 4. Experimenters need to plan experiments based at least partly on physical insight and then update their mental models based on what they observe. (It is interesting to note that the discussion above shows that the students apply this thought process in the airplane design contest). The superiority of such a heuristic approach over 'one-shot' procedures cannot be proven mathematically. This led Box to conclude that 'scientific method is thus mathematically incoherent.' The observations in this paper support Box's message that over-reliance on mathematics and logic can be detrimental in engineering design.

HEURISTICS IN ENGINEERING DESIGN: SUGGESTIONS FOR FUTURE RESEARCH

The previous section argued that engineers use heuristics to plan and analyze experiments for engineering design and that this practice is highly effective. This raises many important questions including: (1) Are there any other heuristics widely used in engineering design? (2) How are engineering heuristics related to other heuristics identified by cognitive scientists?

In this section, we pursue these questions by following the recent formulation of design thinking detailed by Dym *et al.* [14]. Table 3 outlines the analysis followed in this discussion.

Eris has described the 'Divergent–Convergent Questioning Mode' and provided evidence of its importance in engineering design [37]. We note that the students in the paper airplane design contest appeared to employ convergent–divergent questioning very naturally and without prompting and that Fig. 4 is a clear example of this mode of thought [36]. This questioning mode may be well modeled as adaptive application of a toolbox of engineering heuristics. Studies might be devised to test this hypothesis.

Table 3. Outline of engineering design thinking [14]

Design thinking
• Design thinking as divergent–convergent questioning
• Thinking about designing systems – Thinking about system dynamics – Reasoning about uncertainty – Making estimates – Conducting experiments
• Making design decisions
• Design thinking in a team environment
• The languages of engineering design

Dym *et al* [14] emphasize the importance of design conceptualization and the difficulty most approaches have in helping people in this critical task. The importance of analogy in such tasks is well known. In addition, the ABC group has emphasized the importance the implicit analogy with tools (statistical testing, computers) in creating models/theories/concepts [38, 39]. This 'tools as theories' heuristic has a clear analogy in design where the nature of CAD, CAE prototyping have often been at least anecdotally [40] related to the nature of design concepts. It is our experience that *acceptance* of a design concept is dependent upon existing frameworks and tools for imagining the completed design; this acceptance effect is emphasized in [39].

Sterman [41] studied the ability of people to reason about system dynamics. Fairly simple scenarios including stocks and flows can confound people (even highly educated people). A research program to look at this has been suggested by Doyle [42]. From the many studies done by the ABC group to reframe problems such as those used [29] to indicate great weaknesses in human statistical reasoning, the first step would be to truly see if people in their actual environment [17] have such weaknesses. The essential point is that humans developed their toolbox in the EEA (environment of evolutionary adaptation) [18] and if we structure our test and representations to fool them, they can be fooled. But if representations are appropriate, mistakes are not made. We suggest that more research should be conducted to determine whether people are able to reason about system dynamics when placed in a problem setting more characteristic of real-world engineering practice.

Dym *et al.* [14] emphasize the criticality of reasoning about uncertainty as part of the engineering design process. Extensive work by the ABC group [43] has shown that humans do this very well if frequencies rather than probabilities are used. In addition, Clausing and Frey [44] have recently suggested that shifting emphasis away from probability may improve the performance of reliability engineers. More research should be done to assess the effect of abstractions such as those used in probability on the design processes and outcomes of engineers. On the basis of what such research reveals, new design tools (especially for reliability engineering) should be proposed and evaluated.

Linder [45] emphasizes the importance in engineering design of making reasonable estimates of relevant physical quantities. 'QuickEst' or a related method may well be the heuristic used by highly skilled engineering designers to make such estimates rapidly. Further research would be required to establish whether this is the case.

Dym *et al.* [14] discuss decision-making in engineering design. In a more general sense, decision-making is a central focus of the ABC group and the heuristics that they have already identified may already be employed by good designers. Dym *et al.* [14] also emphasize that design is a social process. The ABC group has studied [17] 'Social Rationality', which they treat as a special form of ecological rationality in which the environment consists of con-specifics and that highlights domain-specific behavior and cognition in social environments. It includes study of the utility for cognition and decision-making of emotion, copying, norms, etc. Dym *et al.* [14] emphasize the importance of representation (multiple languages). The ABC group has shown that the way in which humans used vision and they way that they experienced the world (in the environment of evolutionary adaptation) is found to influence the appropriate representation for us to make appropriate decisions now [43]. Thus, the emphasis on multiple representations seems to be in agreement with the basic approach of the ABC group.

This discussion indicates the potential for rich connections between what is known to be important in design and the work of the ABC group. However, we do not want anyone to be mistaken about our view of the completeness of this correlation. We have only outlined a beginning of such thinking because, to our knowledge, the ABC group has not even considered the design process (especially the engineering design process).

CLOSURE

The ideas discussed in this paper are all at a very preliminary stage of development. We take personal observations from the engineering classroom and from industry practice and relate them to emerging results from cognitive science and statistics. Our current belief is that engineering designers use a toolbox of fast and frugal heuristics. The use of this toolbox benefits greatly from adaptation, with more importance given to flexibility in the learning process than formal optimality. Further, the behaviors we observe seem to be highly effective, representing a practice to be encouraged and honed through experience rather than drummed out by teaching formal, systematic design methodology. All of these observations seem to be highly consistent with recent results from cognitive science, particularly those of the Adaptive Behavior and Cognition group. We therefore submit that exploring the implications of fast and frugal heuristics in the engineering design process is a fruitful area for further research. Such heuristics may be a key to understanding the innate human ability for engineering design and the prodigious performance of engineering design so far in history. If the role of heuristics can be verified and quantified, the implications may be significant both for industry as it seeks to improve its design process and for universities struggling to help young people become skilled designers.

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