Is It Time for a New Pedagogy for Engineering Education?

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Abstract

The activity that most distinguishes engineering from mathematics and the physical sciences is the design of technologically challenging devices, products and systems. But, while ABET recognizes design as a decision-making process, our current educational system treats engineers as problem-solvers and delivers a largely deterministic treatment of the sciences. Problem solving and decision making involve significantly different considerations, not the least of which is that all decision-making is done under uncertainty and risk. Secondly, effective choices among design alternatives demand an understanding of the mathematics of decision making, which rarely appears in engineering curricula. Specifically, we teach the sciences but not how to use them. Decision makers typically earn 50-200 percent more than problem-solvers. The objective of this paper is to make the case that this gap in engineering education lowers the value of an engineering education for both the students and the faculty, and to provide suggestions on how to fix it.

Keywords

Decision making, engineering design, systems engineering, uncertainty and risk, engineering curricula

Historical Background

Engineers have been called upon to exercise their design and systems engineering skills for millennia. The Great Pyramid of Giza[1], constructed in the early 26^{th} century BC, rivaled the International Space Station in size, cost and complexity. Rising to a height of nearly 500 feet, the peak workforce during its construction is estimated at 40,000 workers performing tasks such as quarrying stones of 2 to 3 tons in weight, some cut to dimension with sub-millimeter precision, and delivered from distances as great as 500 miles from the site of the pyramid. The base of the pyramid is aligned with the cardinal directions accurate to 0.067 degrees. The Romans built a system of aqueducts that supported a city of over one million, supplying over 500,000 cubic meters of water daily[2]. The ancients also designed and built immense ships. The Syracusia[3], 180 feet in length, had a capacity of 1940 passengers and a crew of 200. It featured a library, gymnasium and bathroom, and could carry a cargo of 1,600 to 1,800 tons. These are achievements that modern engineers would be proud to have made.

But the engineers of these early projects did not have the science, mathematics, computing capabilities or machinery to simplify these tasks. Instead, they were trained as apprentices, working for years under the mentorship of experts. And this appears to be how engineering education proceeded for over four millennia.

The Transition to Engineering Education as Applied Science

To be sure, science and mathematics began to connect to engineering as far back as Euclid and Archimedes. But the connection remained rather tenuous until the 17th century with major contributions by Galileo and Newton. Indeed, Galileo has been credited with establishing the connection between physics and mathematics. But this connection remained largely in the practice of the sciences rather than engineering. Napoleon is credited in the late 1700s with the application of scientific practice to engineering. To this end, he created the French polytechnic, which became the model for American engineering education beginning with the establishment of Rensselaer Polytechnic Institute in 1824[4,5]. Still, although this model introduced scientific principles into engineering education, engineering education continued to have a substantial apprenticeship component and was taught largely by persons with considerable engineering experience. As late as the early 1960s, the nation's engineering faculty was comprised very substantially of persons whose formal education ended at the Masters level.

The seeds of change were planted in 1939, when Karl Compton, then president of MIT stated[6], "*I hope therefore, that increasing attention in the Institute may be given to the fundamental sciences, that they may achieve as never before the spirit and results of research; that all courses of instruction may be examined carefully to see where training in details has been unduly emphasized at the expense of the more powerful training in all-embracing fundamental principles.*" MIT then led the transition from an apprenticeship approach to engineering education to an applied science model. The transition was greatly accelerated by World War II, in which technology arguably played the deciding role, and later by the federal government.

As the War was coming to a close, engineer Vannevar Bush who headed the Office of Scientific Research and Development, which supported almost all wartime R&D, saw continuing support for research in mathematics, science and engineering threatened. In response, he wrote the now famous policy paper[7], "*Science, the Endless Frontier*, in which he argued for stable and long-term funding of scientific research. This paper was the basis for establishment of the National Science Foundation, and expanded the portfolios of the Office of Naval Research, the Atomic Energy Commission and the National Institutes of Health. These agencies comprised a significant new source of funding for academic research in the sciences. I argue that these institutions led to pressure on the nation's engineering schools to take advantage of this new source of funds, and so to the transition of engineering education away from the basics of design and toward the view of engineering as applied science. For example, in the early 1960s, Princeton University renamed the School of Engineering, the School of Applied Science, and the Mechanical Engineering and Aeronautical Engineering departments merged to become the Department of Aerospace and Mechanical Sciences. Similar transitions occurred in many other engineering institutions, in many instances erasing the word "Engineering."

Accompanying this transition, priority for new faculty hires shifted from an emphasis on MS-level engineering experience to PhD-level science. Again, I would argue that the availability of external funding for scientific research helped to drive this transition. During the decade of the 1960s, this shift transformed engineering departments to faculty comprised increasingly of PhD "scientists" devoid of actual engineering experience. And, during the next decades, engineering design was largely eliminated from engineering curricula[6].

The Reemergence of Design

By the mid-1990s, the lack of emphasis on engineering design led to complaints from industry that graduating engineers lacked the skills necessary to fulfill their needs. This led ABET to publish its "Engineering Criteria 2000," which emphasized that[8], "Design and problem-solving skills remain critical objectives." In 2017, the definition of engineering design put into effect by ABET noted, "*It is an iterative, creative, decision-making process in which the basic sciences, mathematics, and engineering sciences are applied to convert resources into solutions*." At this point, design is once again recognized for its decision-making component, although regrettably the result of the process is still referred to as "solutions."

Decision-Making vs. Problem-Solving

A problem typically takes the form of a question posed in search of an answer or solution. The basis for a problem solution is the laws of nature as we know them, logic or mathematical consistency and the data or boundary conditions of the problem. We typically judge a solution to be right or wrong, right if it is consistent with the above basis, wrong otherwise. There is no particular commitment of resources in a solution, and solutions are frequently deterministic. Sometimes we refer to "open-ended" problems, which tend to be problems with no specifically correct solutions such that other candidate solutions are ergo incorrect. But frequently, open-ended problems actually constitute decisions.

On the other hand, a decision is made, not solved[9]. The result of a decision is an outcome, and the components of a decision are alternatives without which a decision is not possible, beliefs on the plausible outcomes of the decision, and preferences over the plausible outcomes. Outcomes are judged based on the preference of the decision maker to be good or bad, not right or wrong. All real decisions are made under uncertainty and risk as outcomes are always in the future, and we cannot predict the future of anything with complete precision and certainty. And all decisions involve a commitment of resources. Indeed, one may consider the commitment of resources to be the decision.

The differences between problem solving and decision making noted above make it rather clear why faculty would prefer teaching problem solving; it is much cleaner. Tests can be objectively graded, for example. Whereas decisions depend on factors including beliefs and preferences that make it reasonable for two persons, each facing the same decision with the same information, to choose different alternatives. Thus, correct responses to test questions from different students need not be the same.

Why are Decision-Making Skills Important?

There are four key reasons why engineers need decision-making skills. First, because the key elements of most engineering activities, such as design, require the engineer to make decisions. Even seemingly small decisions can have very large consequences. For example, the decision not to use redundant attitude sensors on the Boeing 737 MAX resulted in two accidents that cost 346 lives at a cost to Boeing of at least $60 billion[10]. Engineers need to fully understand the consequences of the decisions they make and how to rationally consider the risks they are taking in making these decisions.

Second, decision makers make more money than problem solvers. Table 1 shows mean annual wages for typical decision makers versus their problem-solving counterparts. These data derive from the U. S. Bureau of Labor Statistics (May 2021), payscale.com and work.chron.com and are approximate. Fair comparisons are difficult to obtain as education levels vary between decision makers and problem solvers, and other factors corrupt precise comparisons. Nonetheless, the data show a distinct trend toward significantly higher salaries for decision makers.

Table 1. Mean Annual Wage for Decision Makers vs. Problem Solvers

Decision Maker	Mean Wage, $	Problem Solver	Mean Wage, $
Family Physician	235,930	Registered Nurse	82,750
Regional Airline Captain	100,000	Regional Copilot	50,000
Major Airline Captain	>200,000	Major Airline Copilot	80,000
Lawyer	148,030	Paralegal	58,330
Law Teacher	130,820	Engineering Teacher	115,590

Third, acuity in problem solving does not infer acuity in decision making. This results in faculty teaching faulty theory and failing to adequately prepare students for their careers. Examples are provided in the next section. The outcome is that graduate engineers are not prepared to apply their knowledge of the engineering sciences optimally, thus lowering their earning potential.

Fourth, emerging world problems demand that engineers be more skilled in decision making. Problems that are becoming critical for survival of the human race include reduction of greenhouse gas emissions, clean removal or reuse of waste products, especially plastics and other non-biodegradable substances, provision of clean water, and provision of clean and environmentally benign energy[11]. These problems demand considerations that go beyond typical engineering measures of system performance.

Examples of Commonly Taught, Faulty Decision-Making Approaches

The Weighted Sum Method: The weighted sum method[12] is perhaps the most popular method of ranking engineering alternatives, most likely because of its clarity and simplicity. Yet, this clarity and simplicity are completely misleading, and the method is almost universally used incorrectly. The method ranks alternatives based on weighted comparison of their attributes, giving a score to each alternative as follows:

$$R = \sum_i w_i a_i \tag{1}$$

where R is the score given to an alternative, the a_i are the scores given to each attribute, and the w_i are weights applied to the attributes, typically taken as the relative importances of the attributes. It follows that, for alternatives A and B, if $R_A > R_B$ then alternative A would be preferred to alternative B or conversely, if $R_B > R_A$, then alternative B would be preferred to alternative A. Further, if $R_A = R_B$ then alternative A would be indifferent to alternative B. It is this equation that determines the weights, w_i. In short, the weights define an indifference surface and have no direct relation to the relative importances of the attributes. Secondly, Eq. 1 is valid only if the attributes are linearly independent, that is, if the value associated with one attribute is independent of the values associated with all other attributes. This is not often the case. And further, the attribute values must be a linear function of the attribute measure. If not all of these conditions are met, the resulting ranking of alternatives is meaningless.

The Pugh Method: The Pugh method[13] assumes that an optimal product design is obtained by optimizing each attribute independently. This assumption is patently incorrect. The following example illustrates this.

Table 2. Pugh Design Optimization Example

Customer	Attributes					
	Attribute 1		Attribute 2		Attribute 3	
	Design 1A	Design 1B	Design 2A	Design 2B	Design 3A	Design 3B
John	Hate	Prefer	Prefer	OK	Prefer	OK
Pam	Prefer	OK	Hate	Prefer	Prefer	OK
Hank	Prefer	OK	Prefer	OK	Hate	Prefer
Preference	1A		2A		3A	

Three potential customers, we refer to them as John, Pam and Hank, seek a product that has three key attributes, such as size, weight and color. Each attribute has two potential designs. John hates Attribute 1 if its design is 1A, and will not purchase the product if this design is chosen. He strongly prefers 1B. He also prefers 2A and 3A, but considers 2B and 3B acceptable. Similarly, Pam hates Attribute 2 design 2A, and will not buy the product if this design is chosen. Lastly, Hank hates Attribute 3 design 3A and will not buy the product that includes this attribute design. Yet, by majority vote of the customers, the Pugh method provides that design 1A-2A-3A is the best design, while we see that none of the customers would purchase such a product. On the other hand, the design 1B-2B-3B is acceptable to all three customers. This example shows how the Pugh method can fail in the simplest and most rational of cases.

Customer Surveys:[9] We currently emphasize to our students that we should rely on customer surveys in order to make “informed” design decisions. But, as the following example illustrates, customer surveys don’t always provide useful information and can, in fact, provide rather damaging information. A manufacturer of little rubber balls seeks to make balls in a color most popular among its young customers. So, the manufacturer conducts a survey of 100 local children asking, “What is your favorite color ball: red, green, orange, yellow or blue?” The result is that Red gets 45 votes, Green 25 votes, Orange 17 votes, Yellow 13 votes and Blue no votes at all. Clearly, red is the most popular color—or is it? Suppose that the underlying color preferences of the children are as given in Table 3.

Table 3. List of Color Preferences from 100 Children Randomly Sampled	
Number of Children	Color Preference Order
45	RBYOG
25	GBYOR
17	OBYGR
13	YBOGR
0	BYOGR

This table shows that 45 children have the color preference order: Red $\succ$ Blue $\succ$ Yellow $\succ$ Orange $\succ$ Green, where the symbol $\succ$ is read, "is preferred to." And likewise for the remaining children. With this preference information, which is not solicited in a typical survey, we can look at pairwise comparisons to see that Blue is preferred to Red by a vote of 55 to 45. Blue is also preferred over Green by a vote of 75 to 25, over Orange by a vote of 83 to 17, and over Yellow by a vote of 87 to 13. In fact, for this particular set of preferences, Blue is the preferred color even though it received zero votes, and Red is the least preferred color. Of course, this is just one possible set of preferences, and there is a huge number of alternative preference sets. But, the bottom line is that this survey provides no useful information, and this is most often the case with such surveys.

One may ask if there is a better way to aggregate survey data. There is a better way, namely a Borda count[14]. But to do a Borda count, preference order data such as that shown in Table 3 must be collected and, because the number of items that must be ranked, that is most often not possible for real design cases. Furthermore, the Borda count is not infallible. Arrow's Impossibility Theorem[15], which is an aggregation theorem that applies across a wide spectrum of aggregation processes, tells us that no conceivable process is without problems. Indeed, for typical survey cases a "correct" aggregation result most likely does not, mathematically, exist, meaning that any such result would be incorrect.

Quality Function Deployment (QFD): QFD[16] and its associated House of Quality, devised at Mitsubishi's Kobe shipyard in 1972, is widely taught and promoted in capstone design classes. This process determines customer attributes (sometimes represented as requirements) and, by means of surveys, determines attribute preferences. It then creates "objective" measures from which an "optimal" product is determined using the weighted preferences of the customers. This method encompasses all the errors of the above three methods and fails a test of validity on many counts.

Requirements: As noted by the common use of QFD, requirements are widely interpreted as statements of customer wants, needs or preferences. They are most often none of these. In fact, requirements are constraints[17]. They state what is not acceptable. For example, a requirement that says a product must weigh less than 100 pounds is mathematically interpreted as, "the product may not weigh 100 pounds or more." Furthermore, requirements are not an expression of preferences and therefore cannot be converted to a design objective. We like to think that we are teaching our students to do design optimization when we begin by collecting requirements. However, a typical constrained optimization problem can be written in the form

$$\text{Maximize } J(\boldsymbol{x}) = f(\boldsymbol{x}) \text{ subject to } \boldsymbol{g}(\boldsymbol{x}) \leq 0$$

where $f(\boldsymbol{x})$ is a real scalar objective function, which rank orders values of $\boldsymbol{x}$, and $\boldsymbol{g}(\boldsymbol{x})$ are constraints, which in this case include requirements. This formulation shows the clear distinction between the objective function, the purpose of which is to rank order candidate designs thus enabling design optimization, and the requirements, which impose constraints that can only degrade system performance. Most requirements that are not imposed by nature such as $F = ma$ are better incorporated into the objective function so that the design can be optimized without these constraints.

Continuous Improvement: It is important to mention continuous improvement processes[18] as these are part of virtually all design processes, down to and including the design of our engineering curricula. In each step of a continuous improvement process, we make the product better than it was. But, surprisingly, after a series of improvements, it can and often does turn out that the product is worse than when we started. How can a series of improvements make a product worse? It can because the continuous improvement process is a path-dependent process. That is, it is a process whose outcome depends on the path taken to get to the outcome as illustrated by the following example. We begin with a product, S, in its current form (status quo). Three independent improvements are proposed, A, B and C. These improvements can be made independently or in combination, thus resulting in the status quo and seven possible "improved" products: S, S_A, S_B, S_C, S_{AB}, S_{AC}, S_{BC}, S_{ABC}. A continuous improvement team consists of three people, whom we shall refer to as Jan, Pat and Michael, with the preferences as shown in Table 4.

Table 4. Continuous Improvement Team Preferences

Team Member	Member Preference
Jan	$S_{AB} \succ S_A \succ S \succ S_B \succ S_C \succ S_{AC} \succ S_{BC} \succ S_{ABC}$
Pat	$S_A \succ S \succ S_B \succ S_C \succ S_{BC} \succ S_{AC} \succ S_{ABC} \succ S_{AB}$
Michael	$S_B \succ S \succ S_C \succ S_{CB} \succ S_{AC} \succ S_{ABC} \succ S_{AB} \succ S_A$

Pat begins the improvement process by suggesting the addition of improvement A. S_A is preferred to S by a vote of 2 to 1. Thus, it is adopted yielding product S_A. Next, Michael suggests adding improvement B. Product S_{AB} is preferred to S_A by a vote of 2 to one, so this product design is adopted. Finally, the addition of improvement C is suggested and adopted as S_{ABC} is preferred over S_{AB}. So, the final product is S_{ABC}, and each improvement made the product better in the eyes of the product improvement team over the preceding product. Yet, every member of the product improvement team strongly prefers product design S over S_{ABC}. Thus, the continuous improvement process made the product worse than it started.

Continuous improvement processes are path-dependent. This is easily verified if, instead of the first improvement to be made is A, it is B or C. Then, we see that the end result is quite different. Many engineering design processes are path-dependent. Path-dependent problems tend to be NP-hard at best, and quite difficult to solve. Sometimes, they can be avoided, such as by using the Borda count in a voting situation. But, to address problems of path-dependency, one must first understand that they exist.

What do We Need to Teach?

The above examples should make it clear that engineering design decision making is neither intuitive nor simple, and few students arrive at their capstone course well equipped to deal with the decisions they will soon make. It is therefore suggested that they be prepared early in their studies by exposure to the following topics: probability theory, game theory, decision theory, optimization theory and social choice theory. These are not topics that need be taught at the graduate level or even at the junior/senior level. Young children play many games that involve probability and game theory, and they have an intuitive feel for uncertainty. These topics could be taught at a freshman level without the complexity of advanced mathematics. The fundamental concepts of decision theory are introduced at a grammar school level by Lewis Carroll in his book, *Alice in Wonderland*[19, 20]. Indeed, the basic concepts of decision theory are easily understood and, even in their simplest forms offer a blueprint for better decision making. Optimization is generally touched upon in an early calculus class, but it could be better attuned to the problems of design optimization. Finally, the engineering sciences could be taught from the applications point of view. For example, we tend to teach a course called *Statics* largely as finding solutions to the equations $\boldsymbol{F} = 0$ and $\boldsymbol{M} = 0$. In this sterile form, the theory seems to lack application as students are asked to solve problems. Instead, this course could be a course on the design of static structures, integrating the theory with its application and giving the students a chance to practice design decision-making skills in the process. It is suggested that all the engineering science courses could include an element of design and that, further, doing so would make the courses more interesting to the students and provide deeper learning.

Thoughts About Changes to the Engineering Curriculum

We need to think about changes to the engineering curriculum from two points of view, that of the student and that of the professor. From the student's point of view, the courses should be challenging but not overly difficult. Example design cases should advance both understanding of the underlying principles and present decision challenges that warrant some level of optimization. Design contests among the students could raise interest and learning. Perhaps the theory can be introduced within the context of design challenges. Some of the challenges might be introduced as team activities, thus teaching teamwork along with both theory and application.

The basics of probability theory, game theory, decision theory and social choice theory may warrant teaching in an introductory course not tied to an engineering science course. This course would be followed by engineering science courses that provide applications of the underlying theory. Students should be required to focus on experience with applications as the theory takes on meaning only with application.

The problem of transition to a curriculum with a decision-making focus is more difficult with the faculty as many of the faculty teaching the engineering sciences and even the capstone design course have received a problem-solving treatment of the engineering sciences and themselves lack the knowledge needed to teach the decision-related topics noted above. Thus, it may be necessary to provide courses for the faculty in order that they are fully prepared to teach decision-making skills. It may be necessary to seek outside funding sources to support such courses.

Conclusions

Design decision making is the major point of application of the engineering sciences. But appropriate and valid application of decision theory is neither intuitive nor simple, particularly when dealing with uncertainty, which is the norm. As a result of our omission of decision theory from the engineering curricula, few graduate engineers have the knowledge and skills to apply their knowledge of the sciences effectively. Thus, many of them become problem solvers as we have taught them to be, and this reduces their value to themselves, to their engineering profession, to the faculty who taught them and to society at large. Fixing this problem will not be easy, however, as most of the current capstone design faculty are themselves untrained in decision making. Thus, it would appear that a first step will be to educate the educators. It is argued here that this is a valuable and necessary step to the continued evolution of engineering education.

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