

A Pilot Program on Teaching Engineering Design Using Probabilistic Approaches

Authors:

Yin Chen, Stevens Institute of Technology, Hoboken NJ, USA, ychen1@stevens.edu

John Sharon, Stevens Institute of Technology, Hoboken NJ, USA, jsharon@stevens.edu

Sven Esche, Stevens Institute of Technology, Hoboken NJ, USA, sesche@stevens.edu

Constantin Chassapis, Stevens Institute of Technology, Hoboken NJ, USA, cchassap@stevens.edu

Abstract — Engineering design represents a process of decision making under conditions of uncertainty and risk, but today's undergraduate engineering curricula rarely include any principles of decision theory. Even though value theory is a crucial component of the decision making process, these subjects are typically heavily underrepresented in engineering curricula and often treated incorrectly by the engineering community at large. Probability theory, which establishes the basic mathematical tools needed for the proper assessment of uncertainty and risk, is often not presented in an engineering context such as design. This situation calls for a revolutionary shift in design education where practical examples of real design cases are used to illustrate the application of sound scientific principles.

This paper describes our progress in a pilot program that aims to prompt a strategic initiative for the development, implementation and assessment of stochastic modeling and simulation based approaches in engineering design education at Stevens Institute of Technology (SIT). In preparation for a feasibility study in a course taken in the junior year by mechanical engineers, we have constructed a series of design scenarios in which to implement stochastic methods. Lecture materials, MATLAB MS Excel analysis modules as well as student assignments have been prepared. The aforementioned will be introduced into the course as a pilot in the spring of 2005. Upon successful completion of this pilot project, the approach will be implemented in the capstone design sequence in the mechanical engineering department.

Index Terms — Evaluation measures, Monte Carlo simulation, multi attribute decision making, probabilistic design approach, sensitivity analysis

INTRODUCTION

Decision making is an important part of any design process [1], [2]. It is vital for future engineers to have a sound foundation in the fundamentals of this concept. Therefore, it is important to incorporate the tools of statistics and probability into engineering design courses to enhance the undergraduates' exposure to decision making and decision making under uncertainty [5], [6].

Even for experienced management professionals, decision making is often an important and difficult process. As students enter the workforce, some as project management personnel, they are faced with making decisions that can affect themselves, their departments, and even their companies. Not only is it important for an engineer or manager to make the correct decision, but it is also important that he can defend his decision. Management curricula have included decision making methods for decades [2]. Although none of the methods guarantee the best results in all cases, they are, nonetheless, efficient and helpful guidelines. All decision making methods assume that as one becomes more familiar with a subject, one's decision making skills with regard to that subject naturally improve. These methods are merely tools and the ultimate result still depends on the decision maker.

Engineers, on the other hand, are rarely exposed to this topic, even though engineering decisions often involve safety issues that may be much more important than business decisions. Not only would the addition of decision making methods into the engineering curriculum show students how to systematically make a decision, it would also help to create a common language between business managers and engineers. Engineers would be able to explain and defend their decisions in a quantitative way that managers can understand.

For the pilot program, only a limited version of the decision making method will be taught. It will, however, be suitable for handling undergraduate design projects. As with any decision making method, it will help to break down complicated, multi attribute problems into smaller, more manageable ones. Since this will be the students' first exposure to the concept, and it will be embedded in an engineering design class, the scope will be narrower than it usually is in a management scenario. Concepts of probability, which are helpful in modeling decisions involving uncertainty, tolerances, failure rates and other important engineering topics, will also be included.

DECISION MAKING PROCESS - METHOD

The students will first be introduced to probability through a general overview of commonly used distributions such as:

- Normal: used for large samples
- Uniform: used to inhibit round off errors
- Poisson: the limiting case of the binomial distribution
- Exponential: used for modeling events that randomly occur over time

In addition, the students will be introduced to the concepts of modeling and evaluation of multiple occurrences of an event in order to study its behavior tendencies and trends through exposure to the Monte Carlo method. A MATLAB program that incorporates these concepts and functions will then be utilized as an applied model for hands on exploration. This program enables students to create probabilistic models of uncertainties in their design parameters. A sample output of this program can be seen in the illustrative example later in this paper.

In essence, decision making is a structured, quantitative approach that consists of the following points, all of which are explained below.

- Defining objectives and generating options
- Specifying evaluation measures
- Determining value scales
- Grading the options
- Testing the decision using sensitivity analysis

We have prepared a guide and software package that will be distributed to the students. It simplifies the complex, multi attribute decision making process and sets rigid guidelines for the students to follow. This approach has been implemented into a series of automated Microsoft Excel macros. These macros take the students through defining their evaluation measures and options to finding the optimal alternative. These macros are further illustrated later in this paper.

The following five stages provide a structure for students to use as a guide through their decision making process.

Stage I: Design Stage

The design stage is comprised of three steps. The first step is to determine the objectives of the project. In addition, one must incorporate any constraints which may limit the design options. A design option is a specific way to achieve the objectives. All possible design options form the option space. In the second step, one must determine a set of options from the available option space. Lastly, relevant parameters and variations for each option in the set must be specified.

Stage II: Evaluation Measures

Based on the design objectives, constraints, their associated parameters and variations, one creates a list of evaluation measures (EMs), numerical quantities that allow one to grade some aspect of the design. Of the EMs in the list, a test of importance must then be performed on each. An EM should be eliminated if varying its outcome from best to worst does not change the outcome of the decision.

There are two types of EMs: probabilistic and deterministic. A probabilistic EM is one whose value is expressed as a range or distribution, i.e. "length is 2.5 ± 0.01 meters for option X." A deterministic EM is one whose value is fully expressed as one number, i.e. "frequency is 0.8 GHz for option Y." If one has any doubts about the scoring of an EM, one should model that EM as probabilistic with tolerances that appropriately reflect his uncertainty. Otherwise, the deterministic model is sufficient. Regardless of the type of EM, one should determine if higher or lower values are more favorable. For probabilistic EMs, one must also determine his risk inclination.

There are three possible risk inclinations: risk averse, risk neutral, and risk seeking. A risk averse decision maker is one who, with a higher is better EM, would use a lower value than expected for the decision in order to be "on the safe side." A risk neutral decision maker would not alter the nominal value, and a risk seeking decision maker would use a higher value. In addition, one must also choose the extent of his inclination. Both the inclination and the extent are modeled by the parameter " α ." For the risk averse case, α is positive. For the risk neutral case, α is infinite. For the risk seeking case, α is negative. As the absolute value of α approaches zero, the risk inclinations become more extreme. The variable α is used as an input in the value functions of the EMs as described in Stage IV.

Stage III: Determining Value Scales

For each EM defined in the previous stage, one must set a range for the option scores. An option score is the value attributed to a particular option for a particular EM. All option scores must fall between the selected “high” and “low” values of the EM. Any option that does not meet this criterion is disqualified. For a deterministic EM, one then determines the score of each option. For a probabilistic EM, however, a few more steps must be completed.

For each option in a probabilistic EM, one must produce a distribution for further calculations by either the Monte Carlo or another statistical method. From the distribution, one can derive the mean, the standard deviation, or any other statistical parameter that may be helpful for further analysis, depending on the distribution. This information will then be used to set a certainty equivalent, i.e. a pseudo expected value or score that is adjusted according to one’s risk inclination.

Stage IV: Determining Option Grades

For each EM, the scores determined in Stage III are scaled or normalized with regard to their range, using the following value formulae.

$$f(score) = \frac{score - Low}{High - Low} \quad (1)$$

$$f(score) = \frac{High - score}{High - Low} \quad (2)$$

$$f(score) = \frac{1 - \exp[-(score - Low)/]}{1 - \exp[-(High - Low)/]} \quad (3)$$

$$f(score) = \frac{1 - \exp[-(High - score)/]}{1 - \exp[-(High - Low)/]} \quad (4)$$

With deterministic EMs, Eq. (1) is used if higher scores are more favorable. Eq. (2) is used if lower scores are more favorable. Similarly, Eqs. (3) and (4) are used for probabilistic EMs, Eq. (3) for a preference of higher scores and Eq. (4) for a preference of lower scores.

Once all option grades are computed for each EM, the next step is to find the final grades of each option. This step consists of two parts. The first part is to find the weight of each EM and the second part is to combine all the previously gathered information to compute the final option grade.

The weight of an EM measures its impact on the overall decision. Each weight must have a value between 0 and 1, and all of the weights must sum to 1. There are three methods for determining weights: arbitrary, direct, and indirect. The arbitrary method should be used when one is familiar with the decision criteria and feels capable of assigning the weights without assistance. The direct method should be used when one knows very little about the decision. One does, however, need to know the ranks of the EMs from most important to least important. Then, a formula is utilized to produce the weights automatically. The indirect method also requires knowledge of the ranks of the EMs as well as a general feeling for the relative magnitudes of the weights. Once the ranks are established, the indirect method represents a series of questions to establish the final weights.

After the weights are determined, Eq. (5) is used to determine the final grade of each option, where k is the number of EMs.

$$FinalGrade = \sum_{i=1}^k Weight_i \times Grade_i \quad (5)$$

Stage V: Sensitivity Analysis

After the final option grades have been determined, it is important to perform a sensitivity analysis. This sensitivity analysis allows one to determine if one has selected appropriate weight values for the EMs. This analysis is conducted by varying the weight of one EM from 0 to 1 while adjusting the weights of the other EMs such that their proportions remain the same. The final grades of each option are computed over the entire range and graphed.

Upon completion, the graphs are analyzed. If the area around the chosen weight contains many line crossings over the optimal option, then one may choose to adjust the weights to obtain a clearer optimum. This analysis is illustrated at the end of the next section.

DECISION MAKING PROCESS — EXAMPLE: TRUSS

To illustrate the decision making process described above, a simple mechanical engineering design problem is solved in this section. The following example goes through the five decision making stages needed to find the optimal setup for a triangular truss. A truss was chosen because it fully demonstrates the functions of the process without being overly complicated.

Stage I: Design Stage

The objective is to design a triangular truss from aluminum that can safely support more than 24,000 N. Figure 1 shows a schematic of the desired design. The option parameters are shown in Table 1.

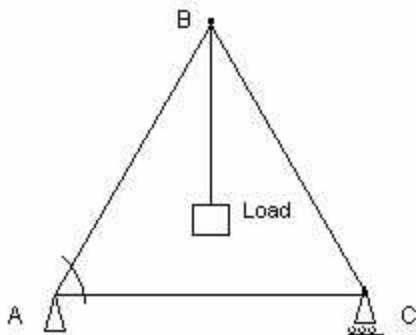


FIGURE 1
DESIGN SCHEMATIC

OPTION	1		2		3	
Fill Type	Hollow		Hollow		Hollow	
Radius (m) Outer/Inner	0.03	0.015	0.04	0.025	0.05	0.035
Radial Deviation (m)	0.005	0.005	0.005	0.005	0.005	0.005
Angle (deg)	65		62.5		60	
Angular Deviation (deg)	0.5		0.5		0.5	

TABLE 1
OPTION PARAMETERS

Stage II: Evaluation Measures (EMs)

For this example, the decision will be made based on three EMs: cost, critical load, and percent failure. Cost is a deterministic EM measured in dollars. It is calculated by the price of the material, and lower values are preferred. Critical load is a probabilistic EM measured in Newtons. It measures the maximum load the truss can support. Higher values are preferred and for safety, is set to 5 (i.e. moderately risk averse). Percent failure is a deterministic EM that is a percentage and dimensionless. It returns the percent of trusses which fail to meet the 24,000 N requirement. It is a measure derived from Monte Carlo simulations of the performance distribution of each option. Lower values are preferred.

A MS Excel macro has been created to assist the student in setting up these EMs for analysis. The basic process is illustrated schematically in Figure 2.

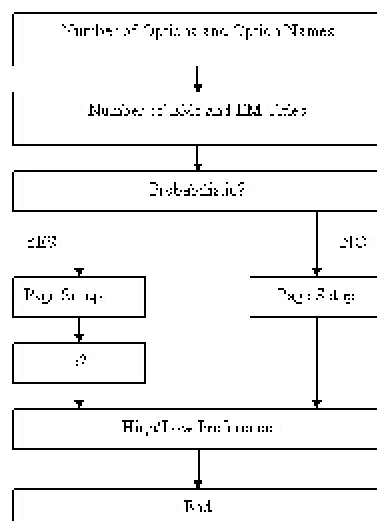


FIGURE 2
FLOWCHART FOR CREATION OF EVALUATION MEASURES

DETERMINISTIC EMS	HOLLOW #1	HOLLOW #2	HOLLOW #3	HIGH	LOW
Cost (\$)	384.14	542.65	682.29	1000	350
Percent Failure	16.97	3.69	3.52	20	1

TABLE 2
OPTION SCORES AND RANGE OF DETERMINISTIC EMS

Stage III: Determining Value Scales

Option scores are then calculated, and a range for each EM is determined. For the deterministic EMs, all that is required are the values in Table 2. For the probabilistic EM of critical load, Monte Carlo simulations were performed using MATLAB, resulting in the distributions shown in Figure 3. 100,000 samples were simulated per option and the relations used for the calculation are Eqs. (6) and (7).

$$I = \frac{\pi \times (r_o^4 - r_i^4)}{4} \quad (6)$$

$$CriticalLoad = \frac{\pi^2 \times E \times I}{L^2} \quad (7)$$

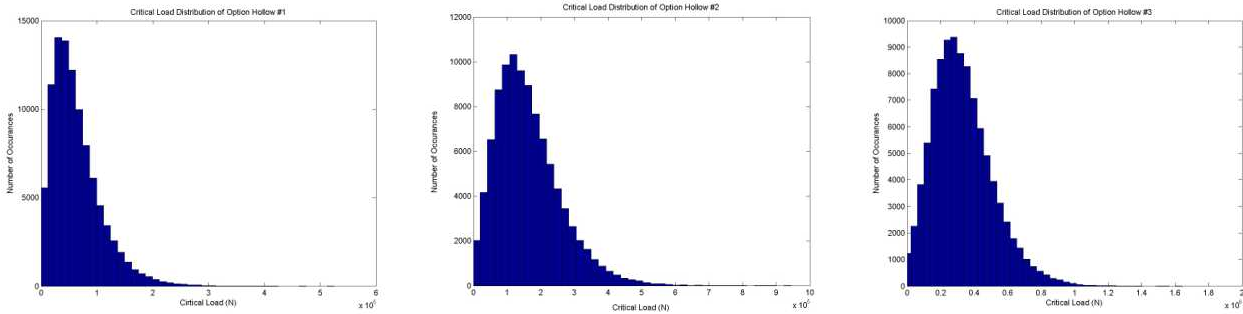


FIGURE 3
CRITICAL LOAD DISTRIBUTION OF EACH OPTION

From these distributions, the certainty equivalent and range were obtained. Figure 4 shows the result of running the EM creation macro detailed in Figure 2 for the critical load EM. The “TARGET” column shows the ranges of the values for the mean MU and the standard deviation SIGMA of each option. The certainty equivalent was obtained by using the function NORMFIT in MATLAB. NORMFIT takes a sample and a confidence level (in this case, 0.95) and returns the possible values of MU and SIGMA of the population from which the sample was chosen. Since this example was based on a risk averse point of view, the lowest possible MU and the highest possible SIGMA were chosen as the certainty equivalent. The numbers in the “RHO” column are the denormalized values of ρ , calculated from the ranges in column “TARGET.” All white cells were automatically filled in by the macro. The blues cells were entered manually and the green cells are optional.

	A	B	C	D	E
1					5
2			TARGET	CERTAINTY EQUIVALENT	RHO
3	Hollow #1	MU		62121	1475000
4		HIGH	3.50E+05		
5		LOW	55000		
6					
7		SIGMA		45669	800000
8		HIGH	2.00E+05		
9		LOW	40000		
10					
11	Hollow #2	MU		1.59E+05	1475000
12		HIGH	350000		
13		LOW	55000		
14					
15		SIGMA		99348	800000
16		HIGH	200000		
17		LOW	40000		
18					
19	Hollow #3	MU		3.25E+05	1475000
20		HIGH	350000		
21		LOW	55000		
22					
23		SIGMA		1.85E+05	800000
24		HIGH	200000		
25		LOW	40000		

FIGURE 4
PROBABILISTIC EM CRITICAL LOAD OPTION SCORES AND VALUES

Stage IV: Determining Option Grades

After the necessary information has been entered, the Excel macro automatically computes the option grades. The results are shown in Figure 5.

	A	B	C	D	E	F
1						
2		SCORE	GRADE			
3	Hollow #1	394.14	0.9321		HIGH	1000
4	Hollow #2	542.65	0.7036		LOW	350
5	Hollow #3	682.29	0.4888			

1						
2		SCORE	GRADE			
3	Hollow #1	16.97	0.1595		HIGH	20
4	Hollow #2	3.69	0.8584		LOW	1
5	Hollow #3	3.52	0.8674			

1					5	
2		TARGET	CERTAINTY EQUIVALENT	RHO		OPTION GRADE
3	Hollow #1	MU		62121	1475000	0.026669104
4		HIGH	3.50E+05			
5		LOW	55000			
6						
7		SIGMA		45669	800000	0.967880179
8		HIGH	2.00E+05			
9		LOW	40000			
10						
11	Hollow #2	MU		1.59E+05	1475000	0.376460928
12		HIGH	350000			
13		LOW	55000			
14						
15		SIGMA		99348	800000	0.652190272
16		HIGH	200000			
17		LOW	40000			
18						
19	Hollow #3	MU		3.25E+05	1475000	0.922544911
20		HIGH	350000			
21		LOW	55000			
22						
23		SIGMA		1.85E+05	800000	0.105721135
24		HIGH	200000			
25		LOW	40000			

FIGURE 5

TOP: SCORES AND GRADES FOR COST. BOTTOM: SCORES AND GRADES FOR PERCENT FAILURE. RIGHT: SCORES AND GRADES FOR CRITICAL LOAD.

The weights of each EM were determined using the rank exponent method (direct) according to [8], where K is the number of EMs, r_i is the rank of the i th EM, and z is the dispersion factor set by the student.

$$weight_i = \frac{(K - r_i + 1)^z}{\sum_{j=1}^K (K - r_j + 1)^z} \quad (8)$$

In this example, the dispersion factor z was set to 0.4. The dispersion factor is a parameter that determines how much the weights differ from the most important to the least important. The higher the dispersion factor is, the bigger is the difference between the weights. This weight method, along with others, has been implemented as a macro in Excel as well. The basic process is illustrated schematically in the Figure 6. The method used in this example is highlighted, and the results are shown in Figure 7.

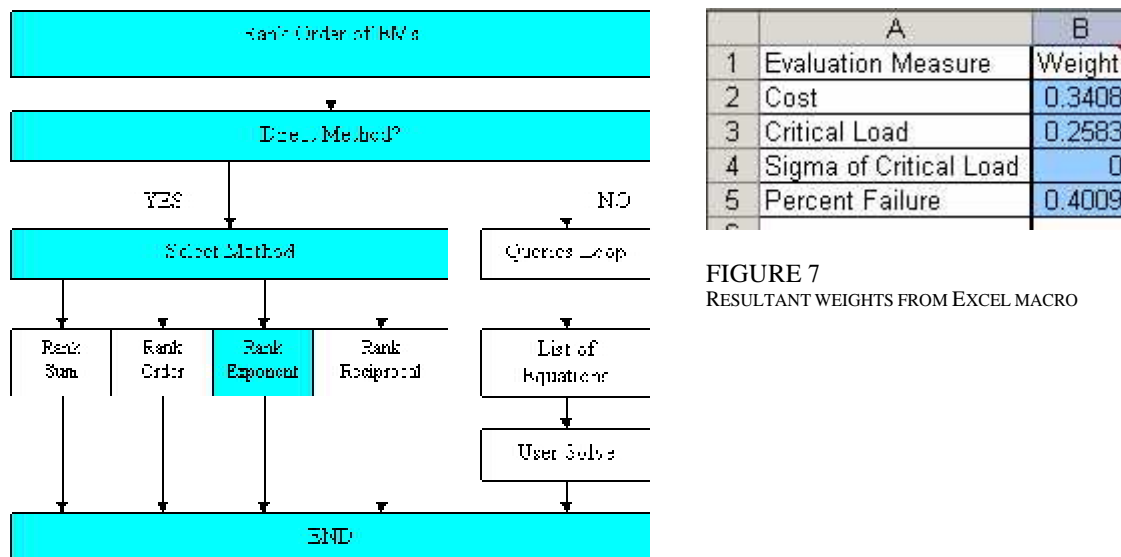


FIGURE 6

WEIGHT CALCULATION FLOWCHART

FIGURE 7
RESULTANT WEIGHTS FROM EXCEL MACRO

Next, the final grade of each option is calculated as per Eq. 5 using a third Excel macro, whose process and results are shown in Figure 8 and Figure 9. “Check Weights” analyzes if all the weight cells are filled in appropriately.

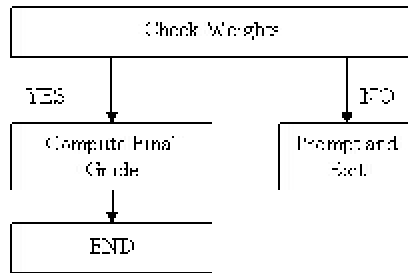


FIGURE 8
FINAL GRADE MS EXCEL MACRO FLOWCHART

A	B	C	D	E	F	G	H
Evaluation Measure	Weight	Hollow #1	Weighted Grade	Hollow #2	Weighted Grade	Hollow #3	Weighted Grade
Cost	0.3408	0.932092	0.317693328	0.703615	0.239819502	0.488785	0.166596817
Critical Load	0.2583	0.026569	0.006863001	0.376481	0.097247882	0.922545	0.238300355
Sigma of Critical Load	0	0.96788	0	0.65219	0	0.105721	0
Percent Failure	0.4009	0.159474	0.063925584	0.858421	0.344101079	0.867368	0.347687663
Final Grade			0.388481913		0.681168464		0.752584835

FIGURE 9
RESULTS OF THE FINAL GRADE EXCEL MACRO

Note that a weight of zero was assigned to the standard deviation (sigma) of the critical load because the percent failure EM already takes into account the spread of the performance distribution.

According to the final grades, option Hollow #3 is the optimal choice.

Stage V: Sensitivity

To check the validity of the weights, a sensitivity analysis can be performed. Figure 10 shows the results of this sensitivity analysis.

The associated sensitivity graphs show that Hollow #3 has the highest final grades over the range of the weights used and none of the graphs contain any ambiguity, which implies that any variations around the chosen weight values would not affect the outcome.

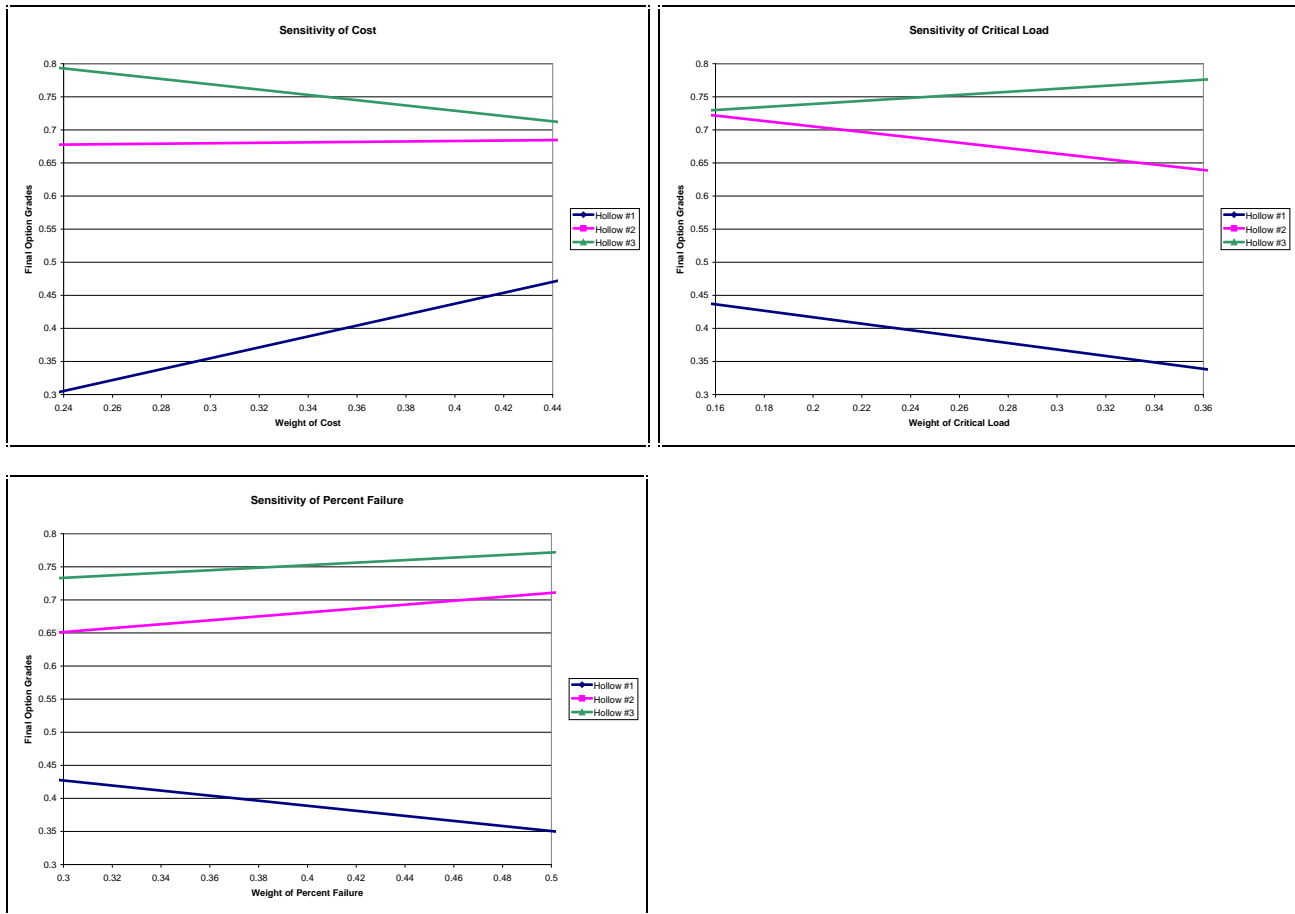


FIGURE 10

TOP LEFT: SENSITIVITY OF COST; TOP RIGHT: SENSITIVITY OF CRITICAL LOAD; BOTTOM: SENSITIVITY OF PERCENT FAILURE

CONCLUSION

This paper describes a decision making process that will be presented to students in a pilot program aiming to develop, implement and assess stochastic modeling and simulation based approaches in engineering design education. Along with lecture notes, various software modules, tutorials and practical examples were developed. The described approach will allow the students to make decisions systematically and enable them to solve complicated, multi attribute decision problems involving tolerances and uncertainty. By including this material in undergraduate engineering curricula, students will gain a new regimented way of approaching an engineering design problem. Although they will only be introduced to a limited version of the decision making process, the students will nonetheless be able to solve any engineering design decision problem within the scope of undergraduate engineering.

ACKNOWLEDGEMENT

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