Assignment #6: Misc. and Advanced Concepts — ME 575

due 4/6/2015 midnight via Learning Suite — 100 possible points

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Objective: Be exposed to optimization under uncertainty and an additional advanced topic of your choice (surrogate-based optimization, or optimization framework usage). Focused on Learning Outcome 7, supporting Outcomes 2 and 8.

Directions: Complete 6.1, 6.2 and **one of the last two problems** (6.3 and 6.4).

6.1 Project Finish strong on your project. During this two week period you should focus on trying to finish up all optimization results. I'd encourage you to start filling in some of the sections of your final report as well. After this homework is turned in you will have just under a week to finish writing your final reports and complete any finishing touches. For this assignment you should report on what you accomplished during the two week period this homework covers.

6.2 Optimization Under Uncertainty

The following problem will give you some experience with the simplified approximation methods for reliability-based optimization discussed in the text. The optimization problem below is a QP for simplicity, but ignore that structure and solve it as a general nonlinear problem so that you could reuse the approach (i.e., use a general nonlinear optimizer and a method for estimating gradients).

For the following problem:

$$\begin{aligned}
\min \quad & f = x_1^2 + 2x_2^2 + 3x_3^2 \\
\text{s.t.} \quad & c_1 = 2x_1 + x_2 + 2x_3 \geq 6 \\
& c_2 = -5x_1 + x_2 + 3x_3 \leq -10
\end{aligned}$$

(a) Find the deterministic optimum.

(b) Find the worst-case, reliable optimum where $\Delta x_1 = \Delta x_2 = \pm 0.1, \Delta x_3 = \pm 0.05$

(c) Now, instead of the worst case tolerances, assume the variables are normally distributed with $\sigma_{x_1} = \sigma_{x_2} = \pm 0.033$, $\sigma_{x_3} = \pm 0.0167$ (these values are $\sigma_i = \Delta_i/3$). Find the reliable optimum where the target constraint reliability is 99.865% *for each constraint individually*. Tables for a cumulative distribution function (CDF) would be useful, but you could also use the *scipy.stats.norm.ppf* function in Python or *icdf* in Matlab.

(d) Compare the *total* target reliability with a Monte Carlo simulation of reliability for all three approaches (using the normal distributions for the input variations).

(e) Briefly discussed any lessons learned.

6.3 Option 1: Surrogate-Based Optimization

Minimize the drag of a supersonic body of revolution using a global polynomial surrogate model. The provided analysis code is somewhat noisy, similar to what would exist with experimental data or with some grid-based simulations, hence the use of a surrogate. The details of this problem are here.

In additional to presenting and discussing your results, discuss lessons learned and whether or not any of the concepts are relevant to your project.

Note: If you select this option you will need to implement it in Matlab. The concepts work just as easily in Python, but we are making use of an external simulation code that was written for use in Matlab, and translating to Python isn't worth it for this one-off example. You can access Matlab on Citrix or any of the CAEDM machines.

6.4 Option 2: Optimization Frameworks

Work with a partner in ME 578 (CAD/Cam Applications) to perform a basic aero/structural beam optimization using the Isight framework. You will use Isight to connect a provided Matlab model, a

CAD program, and ANSYS. Students in ME 578 will provide the experience with Isight and connections to CAD/ANSYS, and you will provide the experience with optimization. If you would like to pursue this option **email me by March 24** so that I can assign you a partner from the other class. The details of this problem are here.

Report your solution, but I am more interested in a description of your process and a reflection on what you learned from the experience.