Report Outline

1 Abstract

1. A mechanical switch involving a spring can have many uses.
2. Depending on the desired use of the spring, an optimal spring will be different.
3. To find an optimal spring we need to have a set of constraints and objectives to optimize.
4. The constraints and objectives are subject to change depending on the use.
5. The objective of this project is to design a flexible optimization routine, that is, flexible in what constraints and objectives are considered.

2 Introduction

1. To be flexible in finding an optimum spring you must allow for constraints and objectives to be interchangeable.
2. There also exists constraints and objectives that are informed by real-world tolerances for design and fabrication.
3. In order to allow this flexibility we employ the use of object oriented programming techniques.
4. In addition, we must be able to find an optimal spring that is subject to constraints, and tolerances that are set by
5.

3 Helical Compression Springs

1. Work done on the design given uncertainty in an acceleration switch, IMECE2011 paper.

Helical springs are a large class of springs sharing the common characteristic of a coiled appearance (see figure). Below is a list of a spring's key design parameters.

1. Spring's inner diameter d_i
2. Spring's outter diameter d_o
3. Spring's coil width d_w
4. Total number of spring coils N_t

5. Pitch p

6. Spring's free length L_{free}

7. Spring's solid length L_{solid}

8. Spring's open length L_{open}

9. Spring's shear modulus G

These various characteristics interact to define key attributes of the spring.

1. **Spring Rate** - this is the effective stiffness of the spring in compression.

$$k = \frac{G}{8N_a(ec)} \frac{d_w^4}{(d_i + d_w)^3}$$

2. **Spring Index** - indicates the distribution and magnitude of stress.

$$C = \frac{d_i}{d_w} + 1$$

3. Coil Binding Gap

$$g = \frac{L_{hard} - L_{solid}(d_w, N_a; ec)}{N_t - 1}$$

4. Maximum Shear Stress

$$\frac{G(L_{free} - L_{hard})}{4\pi N_a(ec)} [\frac{d_w(4d_i^2 + 9.46 d_i d_w + 3d_w^2)}{d_i(d_i + d_w)^3}] < UTS$$

4 Problem Formulation

1. The formulation is informed by many sources...

2. Multiple-Interconnected Dimensions, graph of interconnectedness

3. List the properties and a short description.

4. Illustrate example of optimization, and explain our generalization.

5. Relaxation and Creep

5 Approach to Problem

5.1 Software Design

1. Flexibility integrated into existing optimization.

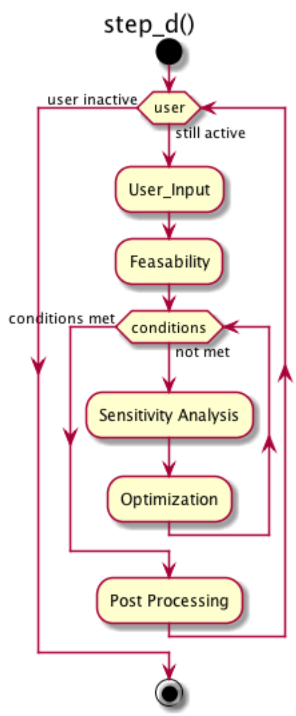
2. Constraint vs. Objective

3. A constraint is an expression that must satisfy an inequality or equality condition.

4. An objective is an expression that can be evaluated.

5. So an constraint can be an objective.

6 Workflow



6.1 Feasibility

1.

6.2 Sensitivity Analysis

As the dimension of design variable space increases, the computational expense of the optimization procedure increases. To reduce the computational expense, it is often desirable to reduce the design variable space by removing the variables that have very little influence on the objective function. Thus, a dimension reduction strategy is required to reduce the design variable space.

Dimension reduction approaches, in the literature have been divided into two categories - (1)filter approach, and (2)wrapper approach. In the filter approach, the input variables are ranked according to a ranking criterion and the most dominant variables can be selected by assuming a threshold influence value. In the wrapper approach, a subset of variables is selected from the list of all possible subsets of the input variables that best estimate the output variable. An optimization technique is used to obtain the best subset of input variables. In this work, the variance-based Global Sensitivity Analysis (GSA), a filter approach, is used for dimension reduction. Note that the input variables represent the design variables for the objective function.

Consider a objective function, G, with n design variables given by x_1, x_2, ... x_n, given by

$$Y = G(x_1, x_2, ...x_n)$$

In GSA, two types of indices can be calculated for each variable - first order index and total effects index. The first-order index (S_i^I) quantifies the uncertainty contribution of an input variable, without considering its interactions with other variables, to the output variable uncertainty. Similarly, the total effects index (S_i^T) quantifies the uncertainty contribution of an input variable by considering its interactions with all variables, to the output uncertainty. The expressions for the two sensitivity indices are given below as

$$S_i^I = \frac{V_{X_i}(E_{X_{-i}}(Y|X_i))}{V(Y)}$$

$$S_i^T = \frac{E_{X_{-i}}(V_{X_i}(Y|X_{-i}))}{V(Y)}$$

Given a design range (lower and upper bounds), a variable can be assumed to be uniformly distributed in the design range. For each variable, the total-effects index is calculated and if it is less than an assumed threshold value, then that variable is assumed insensitive and removed from the optimization procedure. Thus, dimension reduction is implemented for a faster design optimization.

6.3 Optimization

1.

7 Computational Experiments

1. Case Studies

2. Relaxation and Creep

8 Summary and Future Work

1. Computational Inefficiencies

2.

3.

4.

5.

9 References