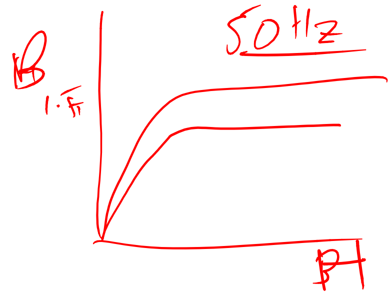
Software Methods and Tools for the Design and Optimization of Electromechanical Devices

Lecture 4: Real World Design Problems

Design in the Face of Uncertainty

Outline

- The real world – Multi-Physics
- The real world – Multi-Objective
- Response Surfaces
- Robust Design



Multi-Physics

- The operation of all real devices includes multiple areas of physics…
- The connection and conversion of electromagnetic energy to other forms is much of the reason for its use:
  - Electrical machines – produce mechanical outputs
  - Actuators – mechanical output, vibration
  - Loud speakers
  - Heating

Multi-Physics

- In some situations, the effects are not wanted and reduce the efficiency of the device in doing its designed work
- Electromagnetic fields can result in forces – often unwanted side-effects
  - Structural problems
  - Vibration issues
  - Acoustic noise

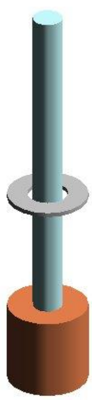
Multi-Physics

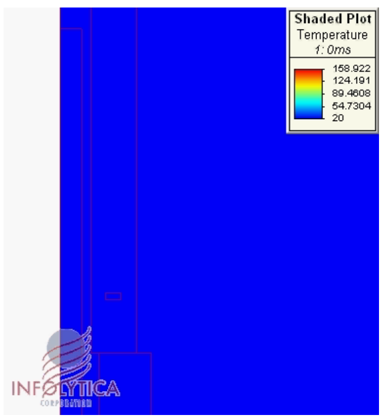
- Electromagnetic fields can result in losses in materials – eddy currents, hysteresis, etc.
  - These result in heating

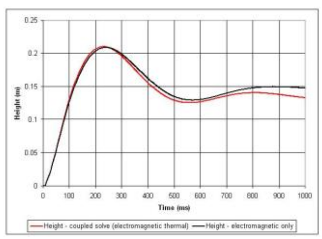
Multi-Physics

- So…
- The analysis of the performance of electromagnetic devices needs to consider other areas of physics
  - Thermal
  - Structural
  - Plus the electrical impact is needed for the drive electronics, i.e. inductances and capacitances…

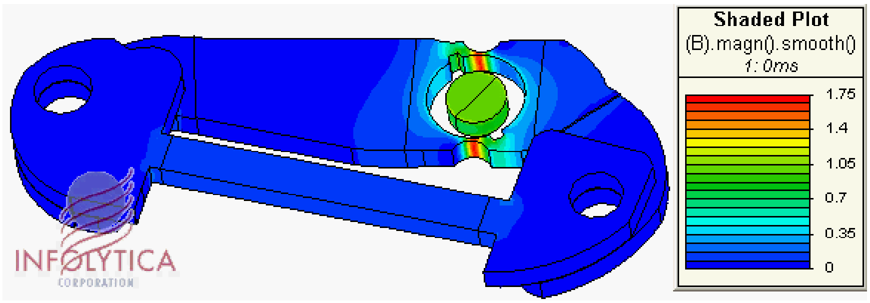
Jumping Ring
Magnetic-Dynamic-Thermal







Watch Motor magnetic-dynamic

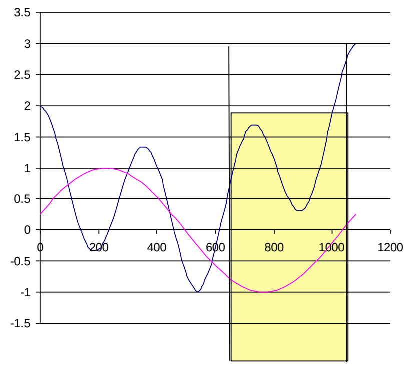


Multi-Objective

- Most real world design problems involve more than one objective or requirement.
- E.g.
  – Minimize the weight of a motor but maximize the efficiency
  – Minimize the cost but maximize the torque generated
  – …
- Often these requirements conflict

Multi-Objective

- What if the design has more than one objective?
  - Minimize cost
  - Minimize losses
- Where is the solution?



A Weighted Sum

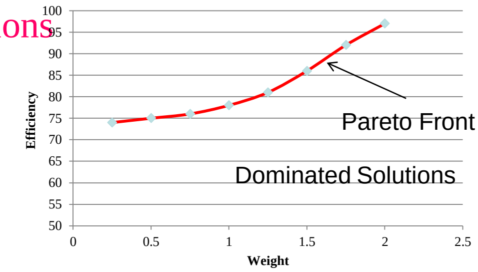
- Pre-specify the choice of trade-off
  - Use a weighting function

$$F(x) = \sum_{i=1}^{n} w_i f_i(x)$$

  - However, the designer has to make the choice at the start rather than having the information to make an informed choice at the end.

The Pareto Front

- Maintaining the choice leads to a *Pareto Front*
- Concept of a *Non-Dominated Solution*
  - One for which a decrease in one of the functions is not possible without an increase in the value of one of the other functions

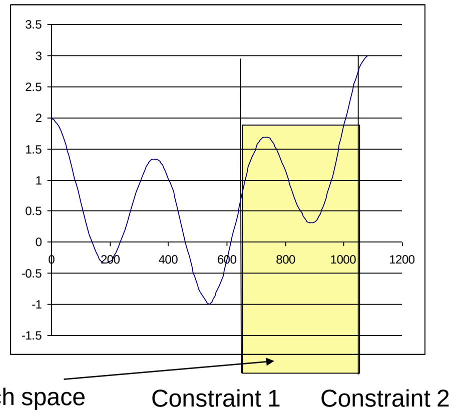


Real World Optimization

- The fundamental specifications for an industrial optimization process are:
  - It finds an *optimal* solution, (one that satisfies the constraints and minimizes a set of objectives)
  - The process will converge to a solution in a minimal time
- Note that the global optimum may not be achievable…

Real World Optimization

- The global optimum may be outside the search space..
  - The specifications are in error
  - The local minimum may be good enough
  - The desired goal may not be achievable



Real World Optimization

- So not a trivial problem
  - We may have constraints which rule out the "ideal" solution
  - We don't know what we are working with
  - We may have conflicting objectives
- And
  - Numerical solutions may be extremely costly to run so we need to run only a few…

Real World Optimization

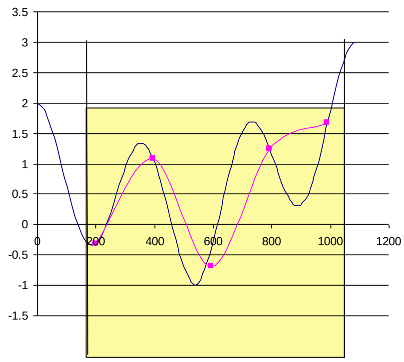
- Approaches
  - Predict where we are going using a deterministic system
  - "Randomly" try for improvements by using a "guided" stochastic search
- Fairly classical stuff
  - How do we do it fast?
  - *The search process is a learning process*

Real World Optimization

- Any iterative process is "learning" about the search space..
  - It is gradually constructing a model based on the data found so far.
  - The construction of the space can be accelerated if something is known "a priori" about the shape
    - E.g. can it be modeled with a simple quadratic?
  - Leads to the concept of a "Response Surface"

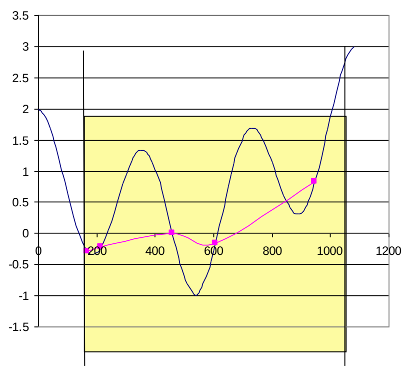
Real World Optimization

- Is there a better way of figuring out the shape of the surface?
  - Sample uniformly
  - How many samples?



Real World Optimization

- Or should they be randomly chosen?



Identifying the Response Surface

- Any algorithm trying to find an optimal point has to work from what it knows of the search space
- It has to be able to decide where to look next
- Single points are a problem – very little information
- So
  - Work with several points
  - Work with a point but more local information

Local Knowledge

- Limited visibility!
  - Really exploits local information about the neighborhood of the point
  - Sensitivity can provide more information
  - Great if near a minimum
  - What about this being a local optimum?

Identifying the Response Surface

- So – how do we get more than just local information
- We need a view of the whole design space?
  - Generate a population covering the search space
- OK – but how many – what about multiple parameters?
  - Too many evaluations could be extremely costly

Identifying the Response Surface

- Compromise
  - Generate a few sample points
    - Latin Hypercube
    - Hammersley Sequence
      - Both from Design of Experiments work
- Generate a surface fit to these points
  - The surface then provides a "cheap" way of exploring
    - *But it is probably wrong!*

Adapting the Response Surface

- So the surface needs to be adapted..
- Rough process:
  – Sample a few points
  – Construct a surface
  – Estimate the position of the optimum
  – Refine the surface in that area by more accurate evaluations

Response Surface Modeling

- Building the surface is known as *Response Surface Modeling* or *Surrogate Modeling*
- Methods:
  – Polynomial Models
  – Radial Basis Functions
  – Kriging
  – Neural Networks
  – Space Mapping

Issues in Robust Design

- Real Devices are not built to the accuracy of computer simulations
- The sources of error are ~~difference~~ dif and, thus, difficult to model
- Manufacturing processes can modify material properties, alter geometric dimensions

Issues in Robust Design

- Tolerances are specified on parameters
  - Devices performing outside the tolerances are not acceptable
- This adds an extra level of complexity into the design of a device

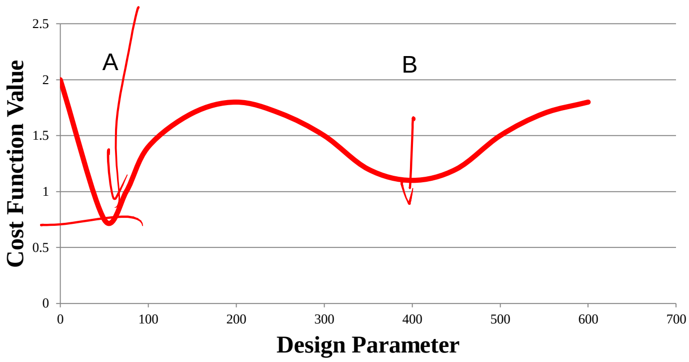
Robustness?

- Real world problems contain uncertainties
  - Often expressed as manufacturing tolerances
  - Property variations
  - Excitation values
- Two robustness issues: the manufacturing issue – inherent in the device; the environmental issue – inherent in the lifetime of the device

Robustness?

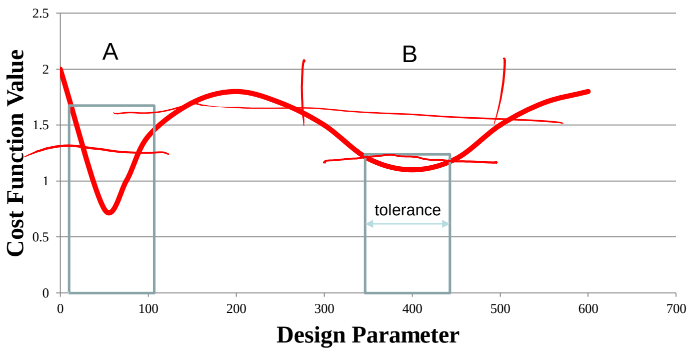
- The performance of an actual device will vary from a simulation prediction because of this
- The issue is "*how can these uncertainties be included in the design process to ensure a minimal performance for a manufactured device?*"

The “Best” Design?



Which is the best design?

The “Best” Design?



Depends on the tolerance specified for the design parameter, the distribution of the tolerance and the “yield” expected.

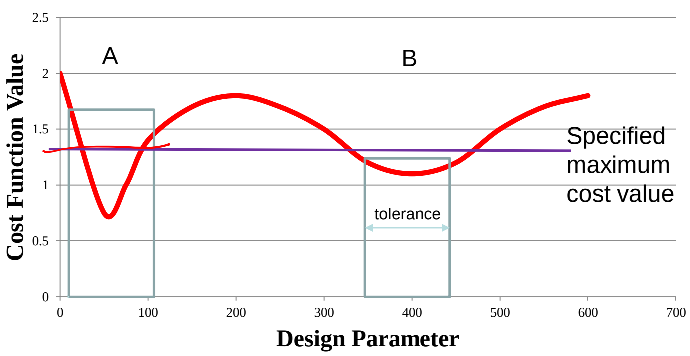
The Robust Optimization Problem

The robust optimum is given by:

$$\min_{x \in X} \max_{u \in U} f(x, u)$$

- f(.,.) is the cost function, x is a vector of design variables, u is a vector of the uncertainty variables.

The “Best” Design?



Depends on the tolerance specified for the design parameter, the distribution of the tolerance and the “yield” expected.

The Robust Optimization Problem

The robust optimum is given by:

$$\min_{x \in X} \max_{u \in U} f(x, u)$$

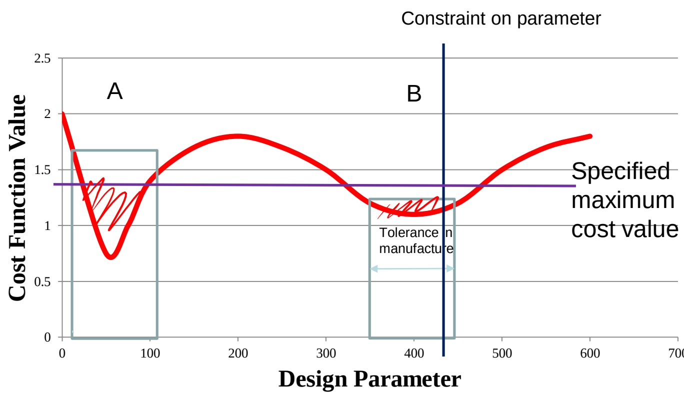
$f(.,.)$ is the cost function, x is a vector of design variables, u is a vector of the uncertainty variables.

Add in the constraint condition, so the optimization is subject to:

$$\max_{s \in S} g(x, s) \leq 0$$

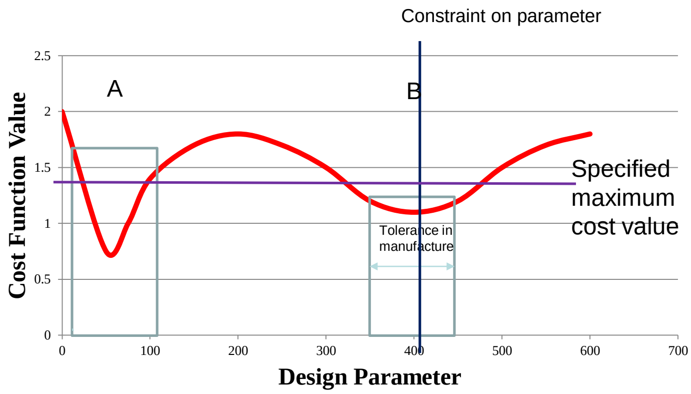
s is a vector of uncertainty variables associated with the feasibility robustness of the constraint function g.

The "Best" Design?



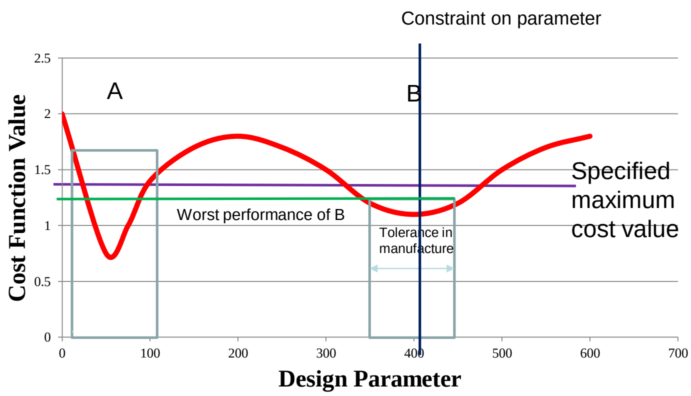
Depends on the tolerance specified for the design parameter, the distribution of the tolerance and the "yield" expected.

The “Best” Design?



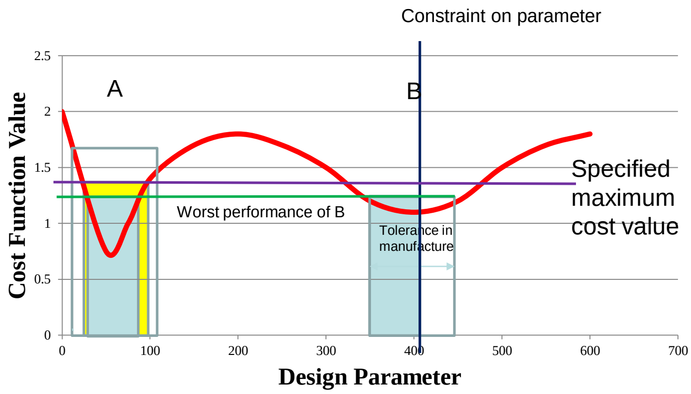
Depends on the tolerance specified for the design parameter, the distribution of the tolerance and the “yield” expected.

The “Best” Design?



Depends on the tolerance specified for the design parameter, the distribution of the tolerance and the “yield” expected.

The “Best” Design?



Depends on the tolerance specified for the design parameter, the distribution of the tolerance and the “yield” expected.

Two Approaches

- Build the tolerance information into the analysis method (“A priori”)
  - The output of the analysis then includes an uncertainty related to the solution
- Explore the objective function space around an “optimal” solution (“A posteriori”)
  - Requires some form of estimation of the function space at multiple points near the optimum

A Priori Approaches

- The parameter tolerances can be built directly into the cost function evaluation so that the optimal solution is generated with an output range determined by the input tolerances.
- For example, techniques based on:
  - Interval mathematics
  - Stochastic finite elements

A Posteriori Approaches

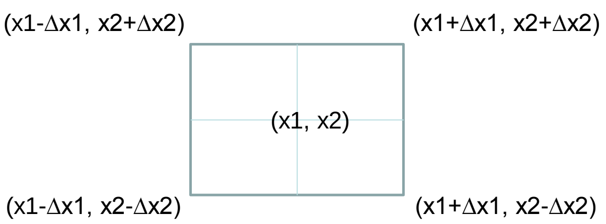
- Develop the concept of a region around an optimum point in the function space which contains all the possible outcomes for the real device
  - The concept of an “Uncertainty Set”

The Uncertainty Set

- Each parameter has a tolerance associated with it.
- The extreme values of the tolerances generate a hypervolume in the objective function space.

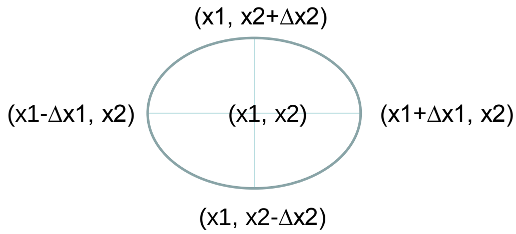
The Uncertainty Set

- A larger version of the finite difference approach to sensitivity
- If the tolerance is uniformly distributed, the volume is a hypercube.



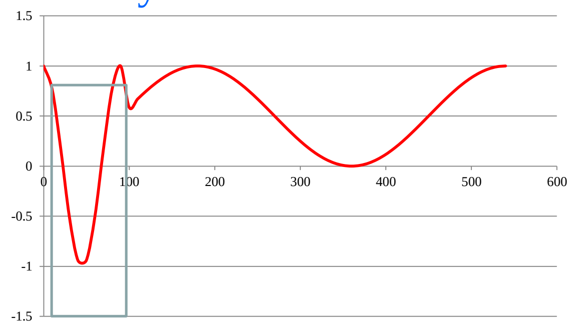
The Uncertainty Set

- If each tolerance has a Gaussian distribution, the volume is a hyperellipse.



Both these systems require a large number of calculations at the vertices of the hypervolumes. This is expensive so an estimate is made of the worst vertex.

- In addition, the worst value of the cost function may not occur at a vertex.



Sensitivity and Robustness

- The sensitivity of the cost function at the optimum point to parameter variations can be computed using CDSA
- The second derivative of the cost function, i.e. the gradient of the sensitivity can be used to judge the robustness of the optimal point.
  - The second derivative is the “gradient index”
- This information can also be used to predict the worst vertex.

Treating Robust Optimisation as a Multi-objective Problem

- The two approaches, i.e. uncertainty set and the gradient index, can re-expressed as multi-objective problems.
- In the uncertainty set, the mean value of the optimum solution and the standard deviation can be treated as two objectives to be minimized.

Treating Robust Optimisation as a Multi-objective Problem

- For the gradient index approach, the optimum value and the gradient index can be viewed as two objectives.
- These can then be treated with standard multi-objective optimization algorithms

Summary

- The concepts from the previous 3 lectures, i.e. simulation, models, virtual laboratories and the design process, have been expanded to include real world issues
- Electromagnetic device design is a complex process involving multi-physics, conflicting objectives and errors in manufacturing
- Design needs to consider robustness issues in addition to the above.