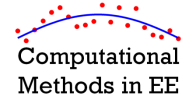




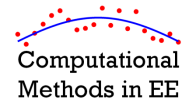
Course Instructor
Dr. Raymond C. Rumpf
Office: A-337
Phone: (915) 747-6958
E-Mail: rcrumpf@utep.edu



Topic 8a – Introduction to Optimization

EE 4386/5301 Computational Methods in EE

Outline



- Introduction
- The Merit Function

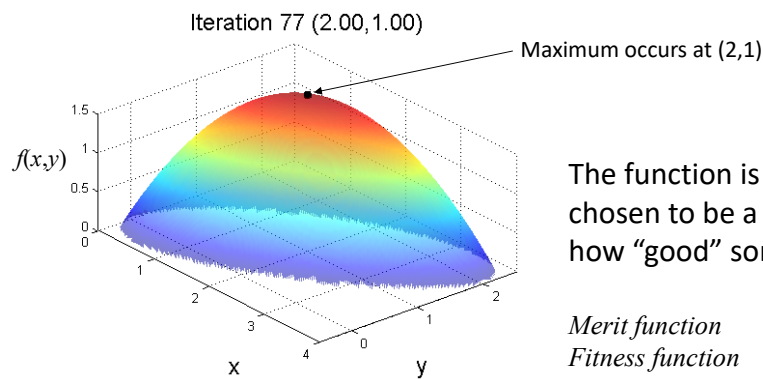
Introduction

1D Optimization

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What is Optimization?

Optimization is simply finding the minimum or a maximum of a function. In this regard, it is similar to root finding.



The function is usually chosen to be a measure of how “good” something is.

Merit function
Fitness function
Quality function
Cost Function

1D Optimization

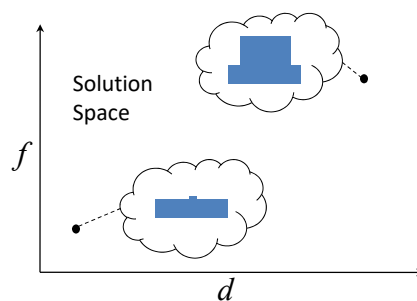
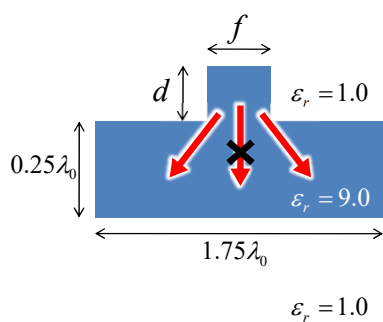
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A Simple Example

Suppose we need to choose f and d so as to prevent diffraction into the zero-order transmitted mode for a normally incident wave.

How do we do this?

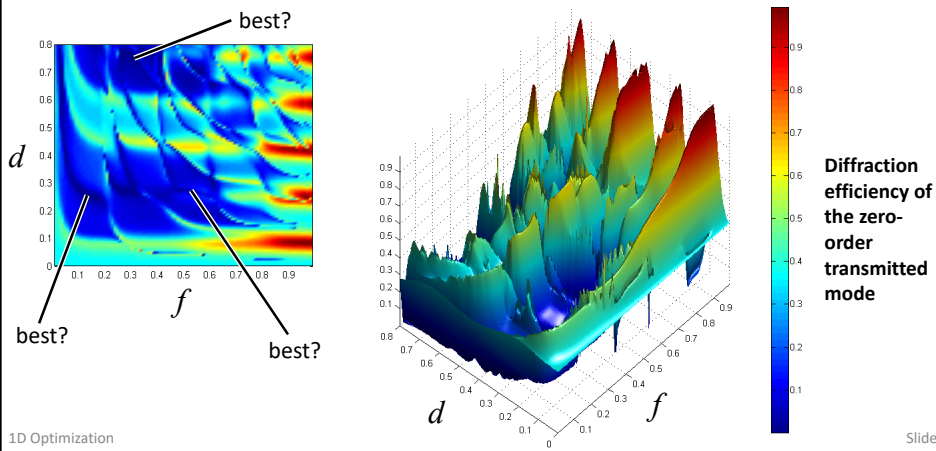


1D Optimization

Slide 5

Global Best Vs. Local Best

The solution space is often sprinkled with many possible solutions (local extrema). It is the primary goal of optimization to find the absolute best solution (global extremum). Without having some apriori knowledge of the solution, however, it is usually impossible to determine if the solution is a global best solution.



1D Optimization

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Common Optimization Algorithms

Computational Methods in EE

- Direct Methods
 - Complete Search ← Only guaranteed method for finding the global extrema.
 - Gradient Methods ← Converges very quickly to a local extremum. No global search.
- Stochastic Optimization
 - Particle Swarm Optimization
 - Genetic Algorithms
 - Simulated Annealing ← Random search to converge to a local best solution.

} Searches globally. Usually finds a good solution. No guarantee it is a global best solution.

1D Optimization Slide 7

Notes on Optimization

Computational Methods in EE

- Stochastic methods are used most effectively when very little is known about the solution space. That is, when the engineer has no idea what the best design will look like.
- Unless something is known about the solution space, it is not possible to certify that the global best solution has been found. As engineers, we are usually satisfied with “good enough” solutions.
- Only an exhaustive complete search can guarantee a global best solution has been found.
- Direct methods converge very fast, but can only find local best solutions.
- It’s all about the merit function, not the algorithm.

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The Merit Function

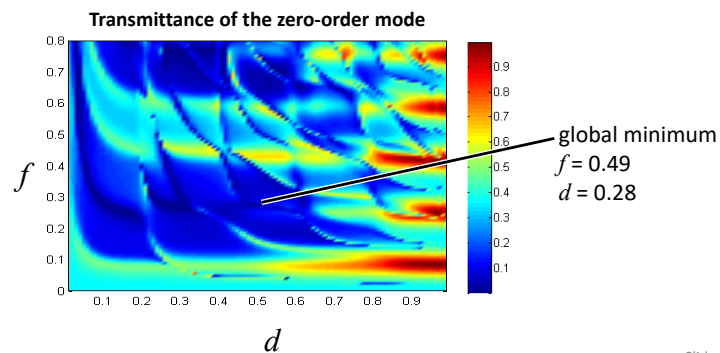
1D Optimization

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The Merit Function

We need a single number that tells us how “good” a particular solution is. This is called the merit function. The optimization can attempt to minimize or maximize this merit function. In this case, our merit function is the diffraction efficiency in the zero-order transmitted mode and we want to minimize it.

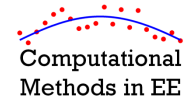
$$M(f, d) = T_0 \equiv \text{transmittance of zero-order mode}$$



1D Optimization

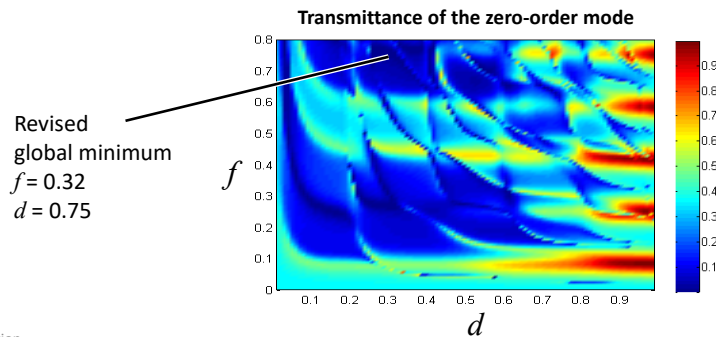
Slide 10

Rethink the Merit Function!!!



In the previous case, the global best was a very narrow region. This probably isn't feasible when fabrication tolerances are considered. It also assumes the model is perfectly accurate. It is often good practice to include some type of "bandwidth" in your merit function to pick a minimum that is also broad and robust.

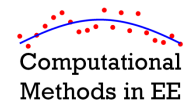
$$M(f, d) = T_0 \div W_0 \quad W_0 \equiv \text{width of extrema}$$



1D Optimization

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Multiple Considerations



The merit function can be challenging to formulate when multiple things must be considered.

There is no cookbook way of doing this. It is up to the ingenuity of the engineer to arrive at this.

A common approach is to form a product where each term is a separate consideration.

$$M = \frac{A_1 \cdot A_2 \cdot A_3 \cdots A_M}{B_1 \cdot B_2 \cdot B_3 \cdots B_N}$$

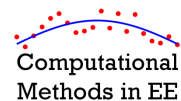
← Parameters we wish to maximize (minimize)

← Parameters we wish to minimize (maximize)

1D Optimization

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Incorporating Relative Importance



If the considerations are not of equal importance, we need a way to enhance or suppress their impact on the merit function.

We usually cannot just scale them by a constant.

$$M = aA_1 \cdot bA_2 \cdot cA_3 = abc(A_1 \cdot A_2 \cdot A_3)$$

There are some other effective ways of doing this.

$$M = A_1^\alpha \cdot A_2^\beta \cdot A_3^\gamma \quad \text{exponents}$$

$$M = A_1 \cdot \log(A_2) \cdot A_3 \quad \text{logarithms}$$

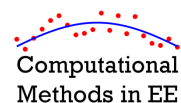
$$M = A_1 \cdot (1 + A_2) \cdot A_3 \quad \text{adding constants}$$

$$M = A_1^\alpha \cdot (1 + A_2)^\beta \cdot \log(1 + A_3) \quad \text{hybrids}$$

1D Optimization

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Example (1 of 2)



Suppose we wish to optimize the design of an antenna.

We are probably most concerned about its bandwidth B and efficiency E . Based on this, we could define a merit function as

$$M = B \cdot E$$

Are these equally important?



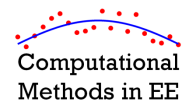
The *Shannon capacity theorem* sets a limit on the bit rate C of data given the bandwidth B of the channel and the signal-to-noise ratio SNR.

$$C = B \log_2(1 + \text{SNR}) \quad \text{This shows that bandwidth and efficiency are not equally important.}$$

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Example (2 of 2)



We can come up with a better merit function that is inspired by the *Shannon capacity theorem*.

$$M = B \log_2(1 + E)$$

Maybe size L is also a consideration. We want data rate as high as possible using an antenna as small as possible. A new merit function that considers size could be

$$M = \frac{B}{L} \log_2(1 + E)$$

This merit function, however, would approach infinity as L approaches zero, leading to a false solution.

This problem can be fixed by adding a constant to L .

$$M = \frac{B}{1+L} \log_2(1 + E)$$