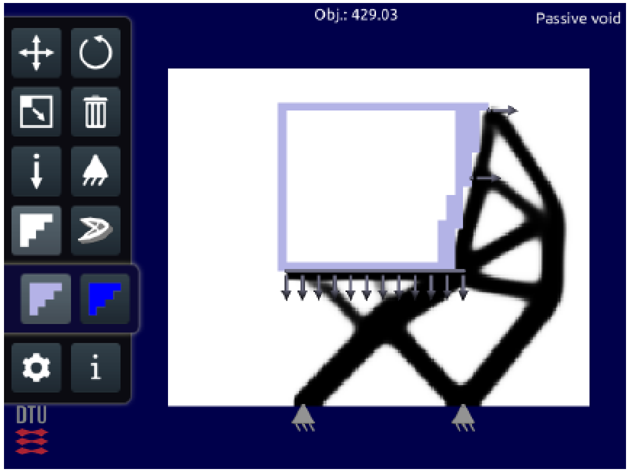
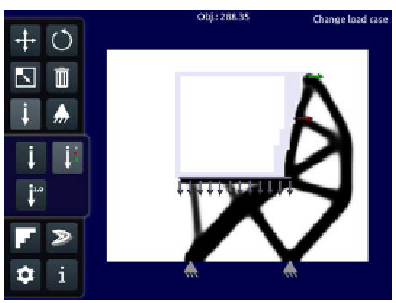
Basics of Topological Optimization software

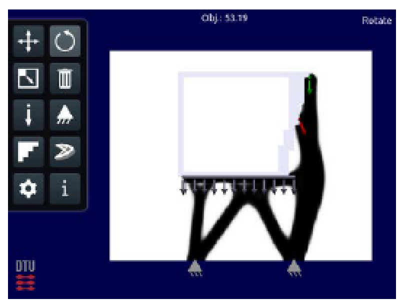
This tutorial is intended as inspiration on how to design a chair with the TopOpt app.



Example 1: The chair design is constructed using a single load case with the following settings: The downward "seat" load is 2.0 times larges than the two right oriented point loads. The volume fraction is set to 0.16 and an passive void domain is included to keep the seat free of material.



Example 2: Effect of making each load a separate load case.



Example 3: Effect of changing the direction of the load cases.

2D TopOpt for Mac

3D TopOpt for Mac

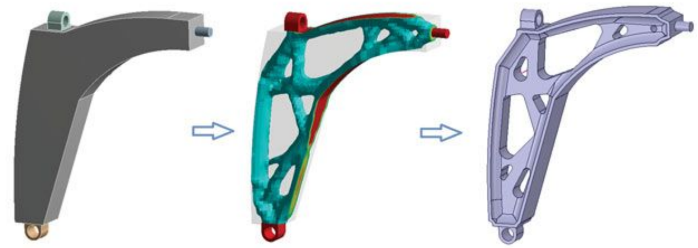
[interactive TopOpt app for handheld devices and web](https://www.topopt.mek.dtu.dk/apps-and-software)

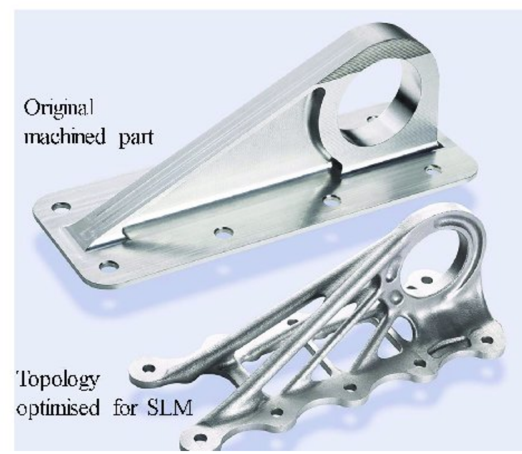
https://www.topopt.mek.dtu.dk/apps-and-software

香港中文大學
The Chinese University of Hong Kong

MAEG5160: Design for Additive Manufacturing

Lecture 4: Digital Design for AM and generative design

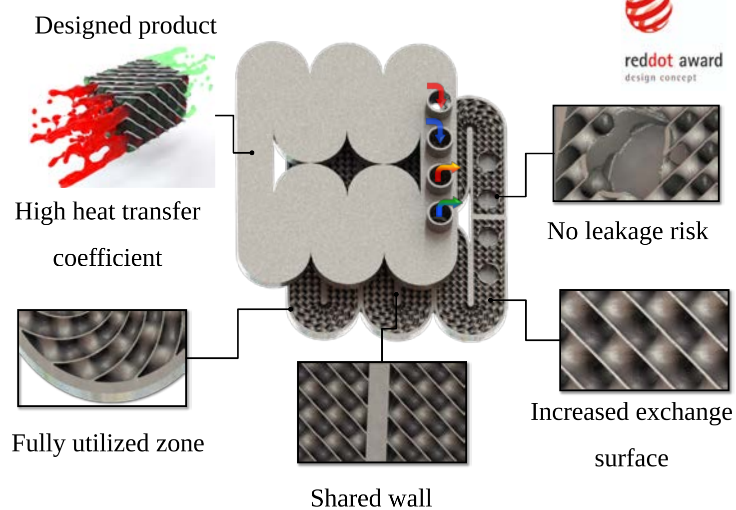




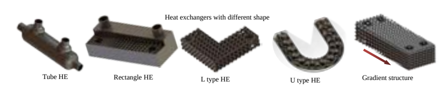
Prof SONG Xu
Department of Mechanical and Automation Engineering,
The Chinese University of Hong Kong.

Past design experience and student award

- 1 FYP won PCKKSCA 2021 Prize UG individual (first runner-up)
- 1 Postdoc won the prestigious Red Dot Award - Design Concept
- Many cabin interior designs are adopted by the Singapore Airline (SIMTech best staff and best industry project award)



3D QR code

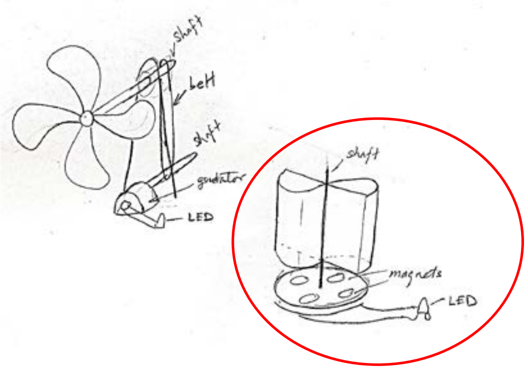


Lecture 4: Digital Design for AM and generative design

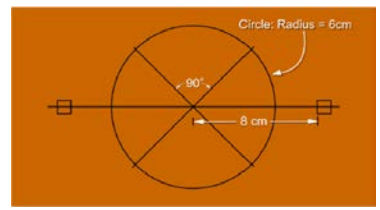
Design specification → Embodiment Design → Detailed Design → Prototyping

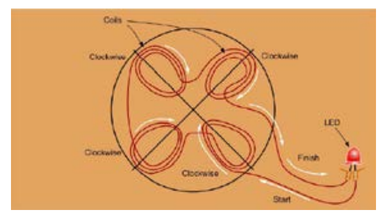
Your company is intended to bid for a job that involves designing a new 1kW wind turbine to be installed on the roof of the SHB building. The designer will be responsible for the design and manufacturing of a prototype with a much smaller scale.

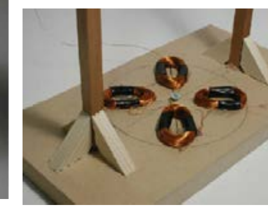
Option A

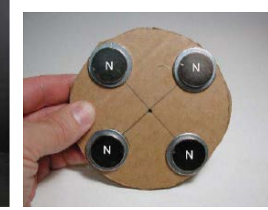


Option B



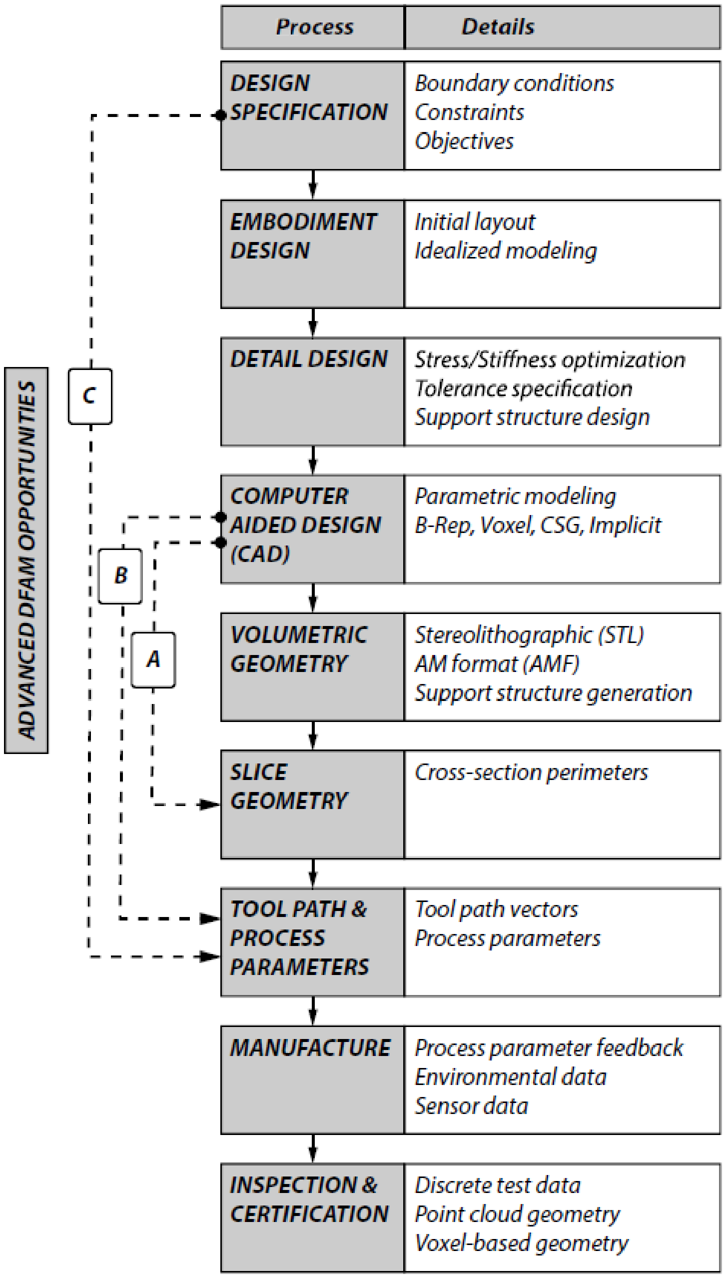






Lecture 4: Digital Design for AM and generative design

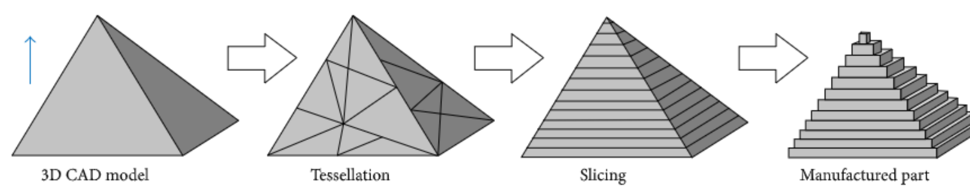
Digital Design process for AM



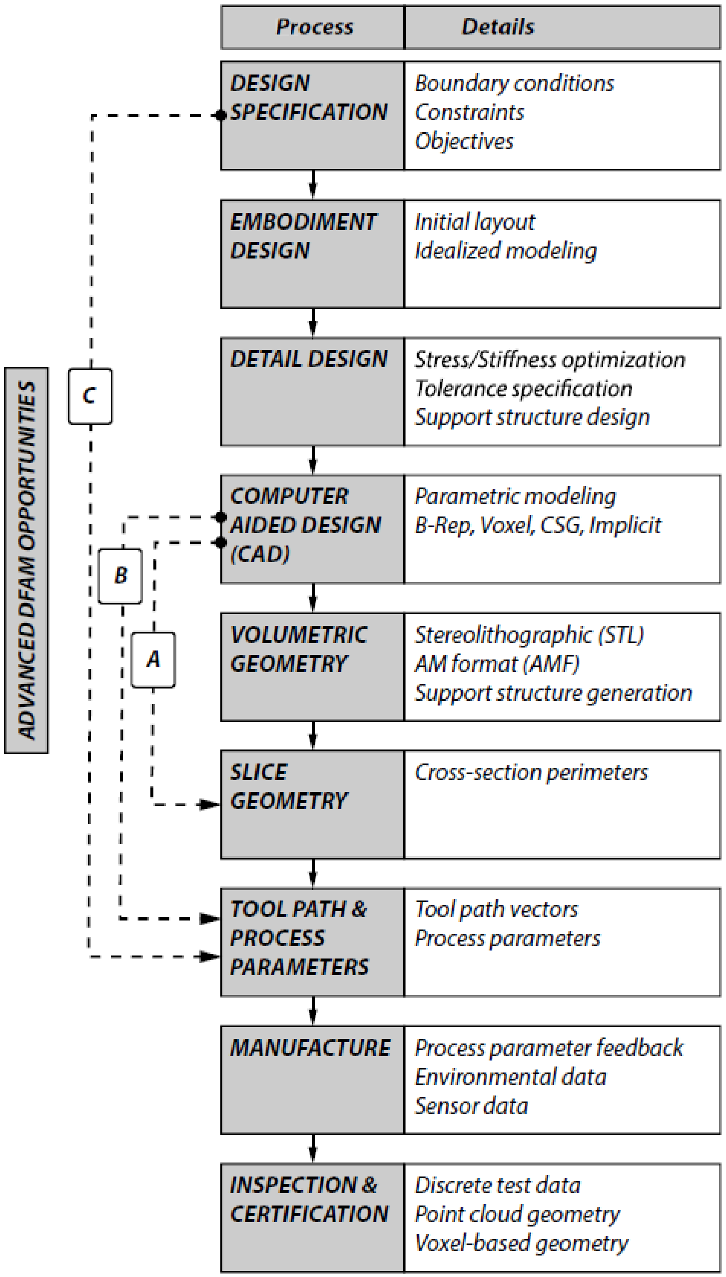
-	INVALID ZONE
M	TYPICALLY MANUAL
A	TYPICALLY SEMI-AUTOMATED

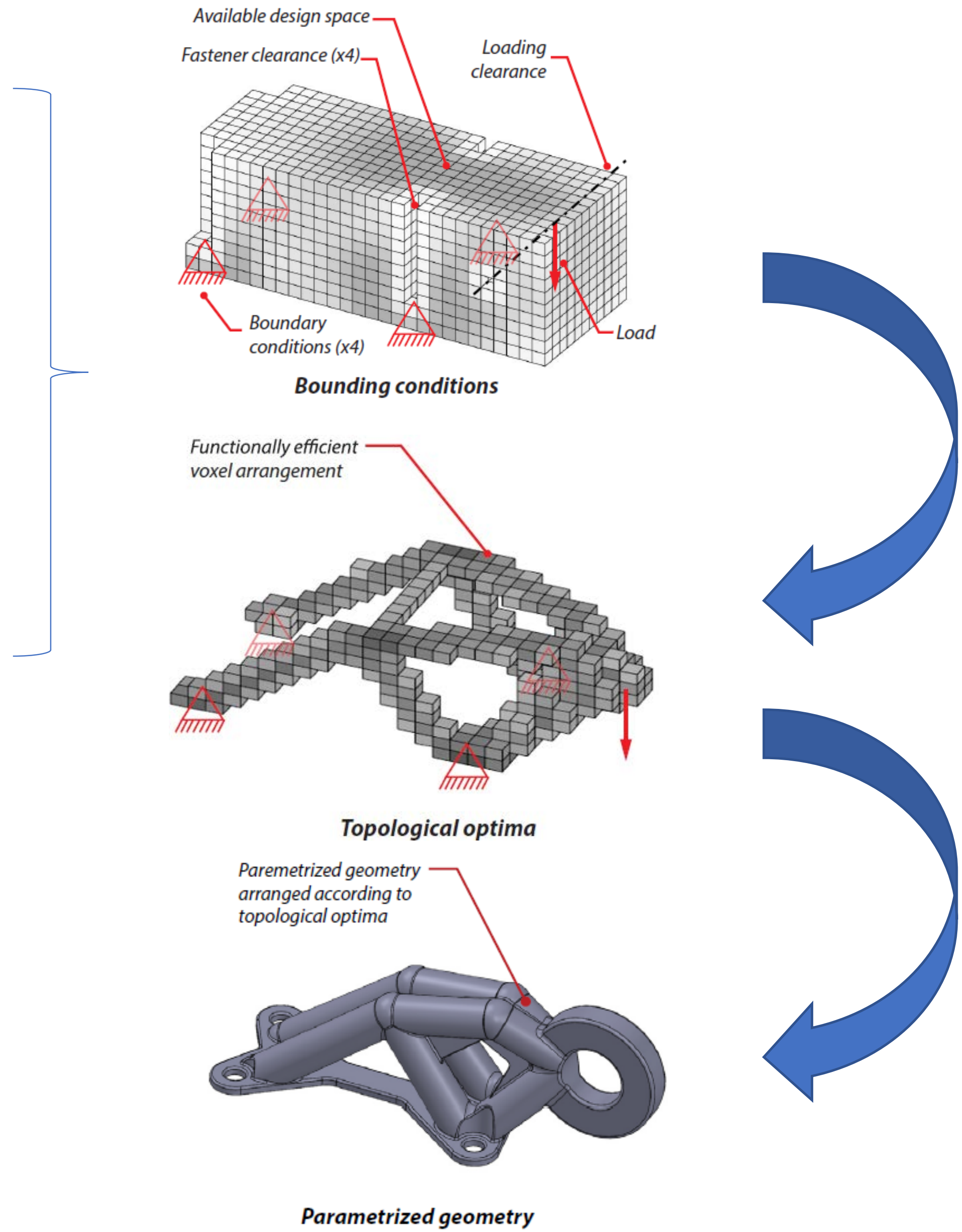
X	ADVANCED DFAM OPPORTUNITY

		Design Specification 1	Embodiment Design 2	Detail Design 3	CAD Data 4	Volumetric Geometry 5	Slice Geometry 6	Tool path & Process Parameters 7	Manufacture 8	Inspection & Certification 9
Design Specification	1	-	M							
Embodiment Design	2	-	-	M				X		
Detail Design	3	-	-	-	M					
CAD Data	4	-	-	-	-	A	X	X		
Volumetric Geometry	5	-	-	-	-	-	A			
Slice Geometry	6	-	-	-	-	-	-	A		
Tool path & Process Parameters	7	-	-	-	-	-	-	-	A	
Manufacture	8	-	-	-	-	-	-	-	-	M
Inspection & Certification	9	-	-	-	-	-	-	-	-	-



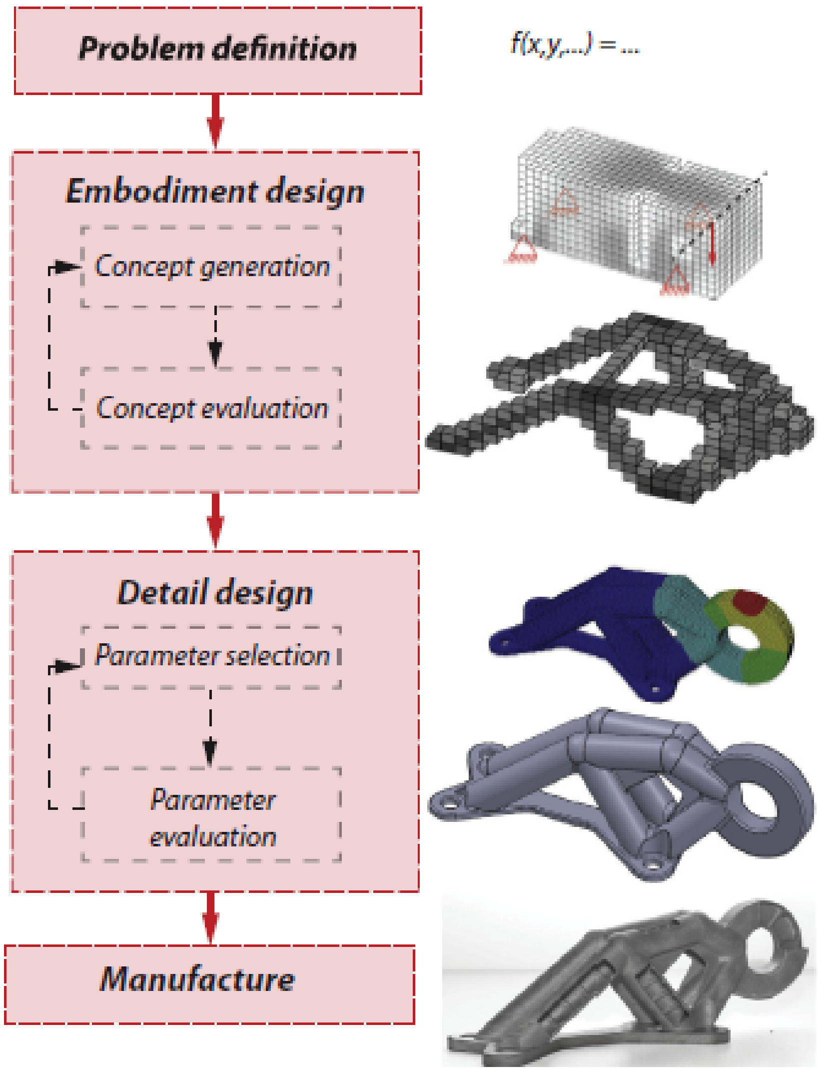
Lecture 4: Digital Design for AM and generative design





Lecture 4: Digital Design for AM and generative design

The term generative design has emerged relatively recently within the design lexicon and is used with varying meaning within different design communities. Generative design can be broadly defined as ‘the rules for generating form, rather than the forms themselves’.



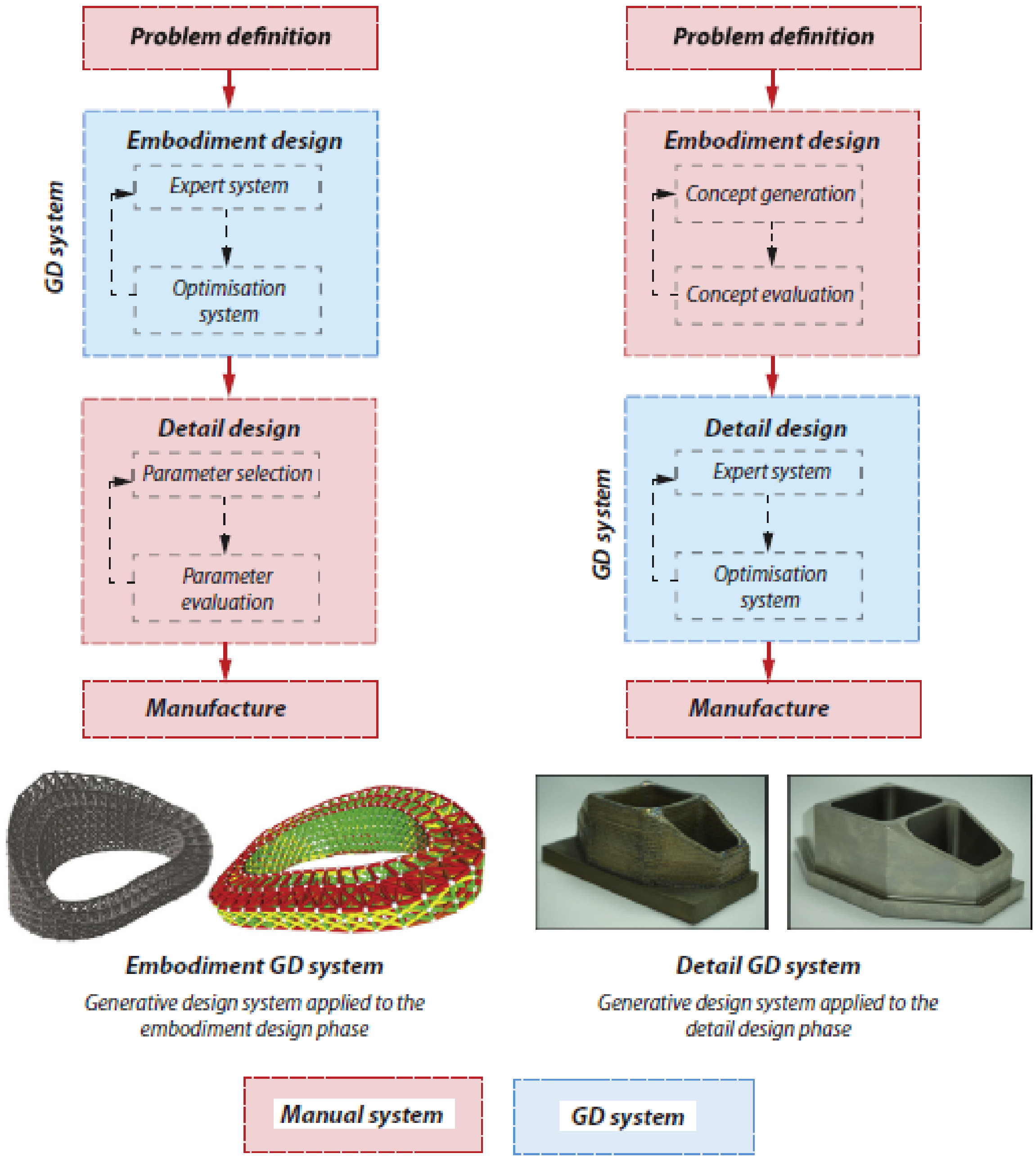
		Optimisation system	
		Generative	Manual
Design phase	Embodiment	Embodiment phase concepts are highly abstract and challenging to algorithmically optimise for complex scenarios.	Manual optimisation at embodiment phase can alleviate the complexity of algorithmic methods. (Case Study B)
Design phase	Detail	Detail phase concepts are more readily characterised and are significantly less challenging to implement with GD optimisation. (Case Study A and B)	Manual detail phase optimisation allows the rapidity of an algorithmic expert system while allowing designer control (Figure 4, Case Study C).

Tabular representation of generative design (GD) system taxonomies. Colour estimates technical risk to implementation: light green - low, dark green - moderate, yellow - high, red – extreme.

Lecture 4: Digital Design for AM and generative design

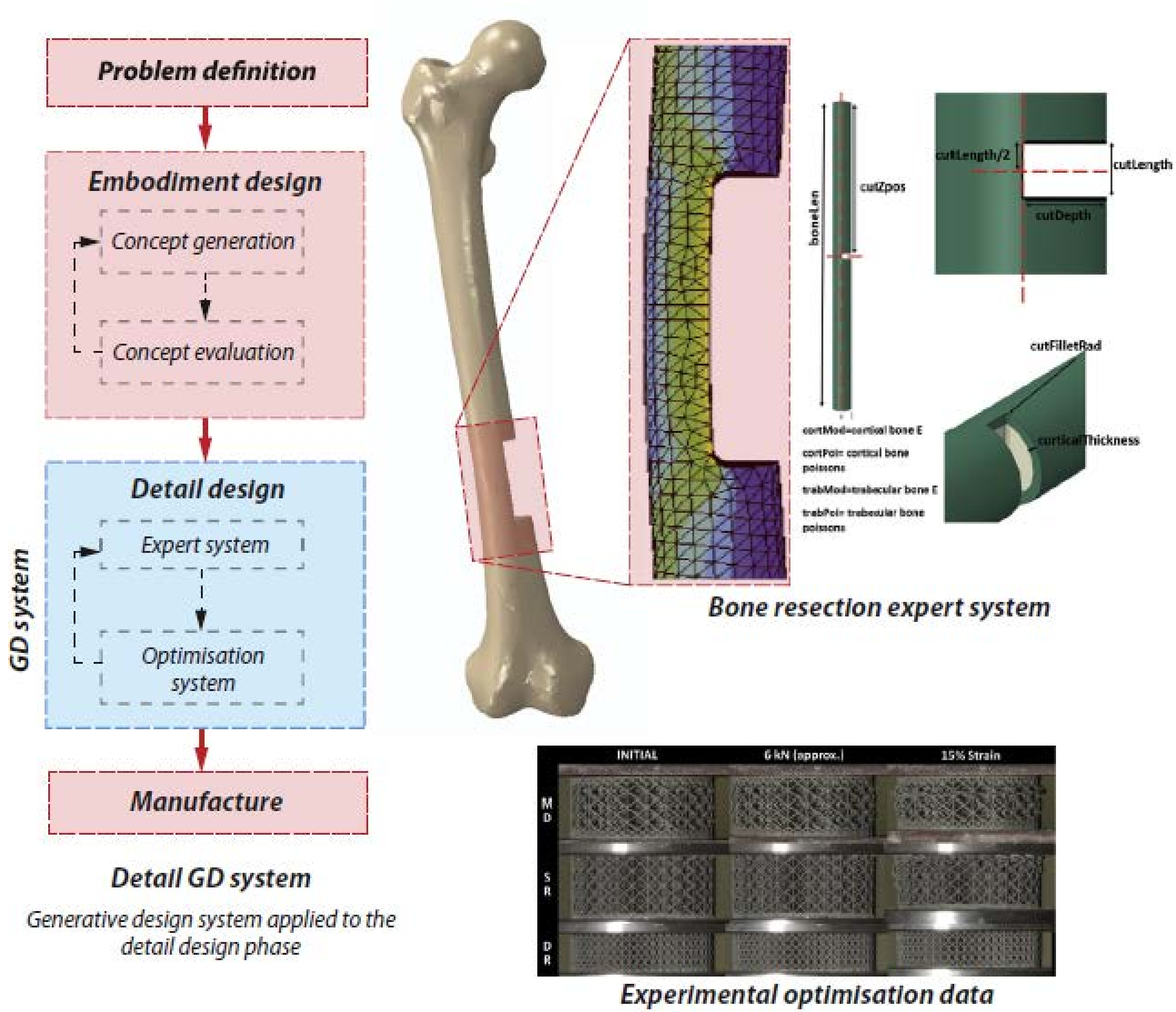
Disparate definitions of the term generative design exist within the literature. Here we define generative design to refer to DFAM tools that utilize autonomous systems to aid in the generation of forms that satisfy a specific set of design requirements. This definition is further constrained such that these generative methods be effective, i.e. they enable some output that is not practically feasible for a human designer.

A fundamental definition of Generative Design architecture must include some element that generates feasible solutions, and another element that evaluates the feasibility of these potential solutions. These elements are referred to respectively as the *expert system* and *optimization system*.



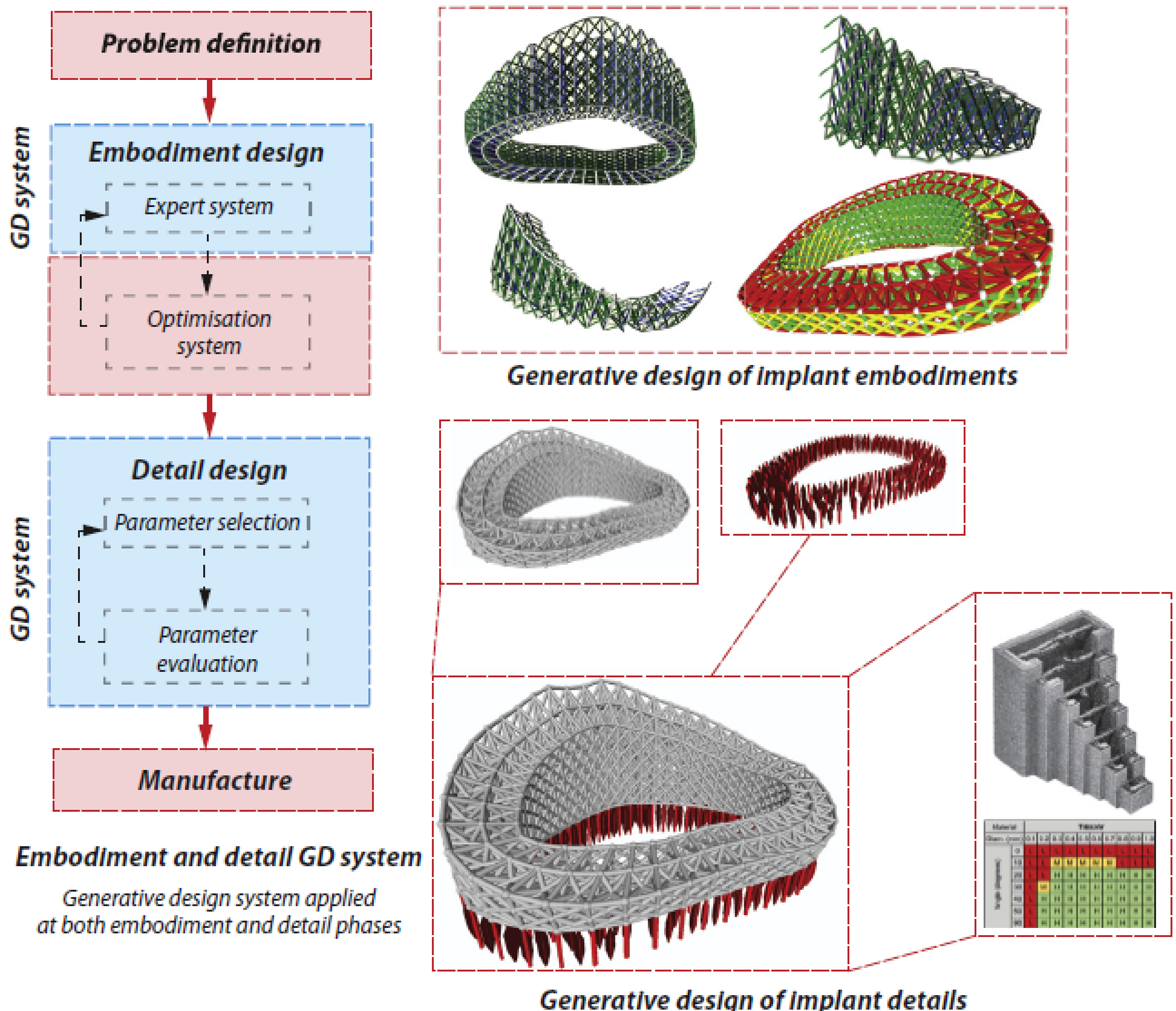
Lecture 4: Digital Design for AM and generative design

Case Study A in the context of the GD system workflow. The GD system (blue highlight) provides an enabling mechanism to generate robust patient specific implants at the detail phase based on predetermined embodiment.



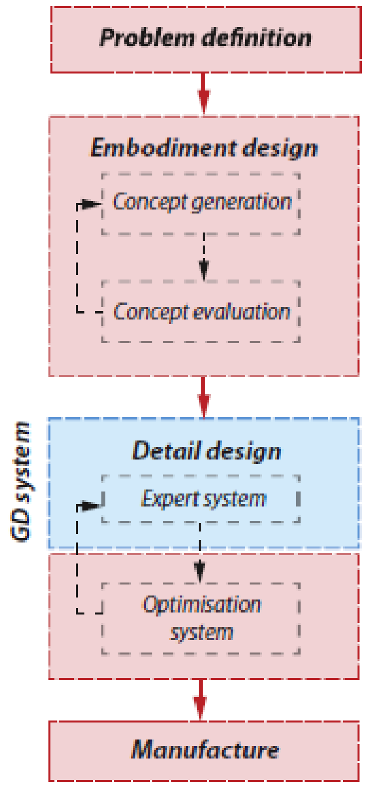
Lecture 4: Digital Design for AM and generative design

Case Study B in the context of the GD system workflow. The GD system (blue highlight) provides an enabling capability at both the embodiment and detail design phases.



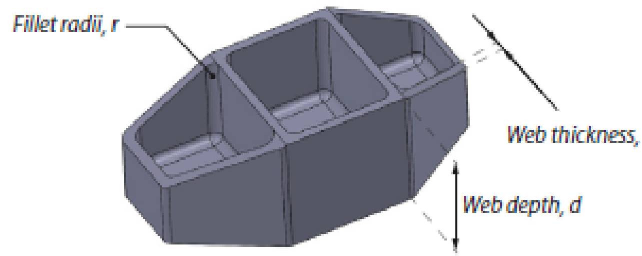
Lecture 4: Digital Design for AM and generative design

Case Study C in the context of GD system workflow. The GD system (blue highlight) provides a mechanism to rapidly embody variants of particular geometry. Manual optimization is currently used but could potentially be implemented as a GD system as DFAM technology and economic benefit evolve.

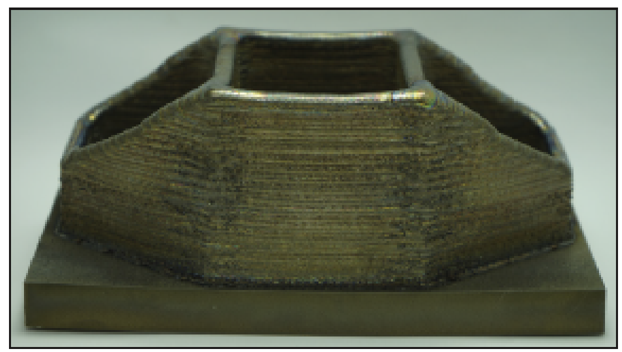


Detail GD system

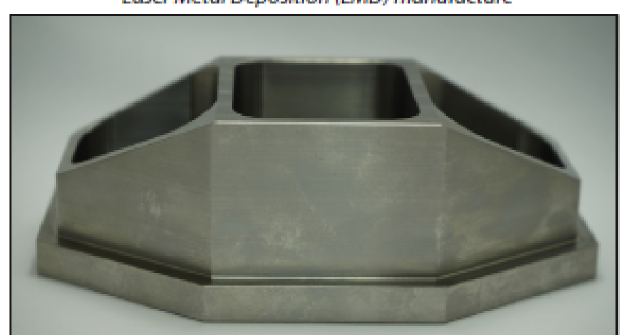
Generative design system applied to the detail design phase



Component detail expert system



Laser Metal Deposition (LMD) manufacture



Post-LMD machining

Manual optimisation of detail for AM manufacture

Lecture 4: Digital Design for AM and generative design

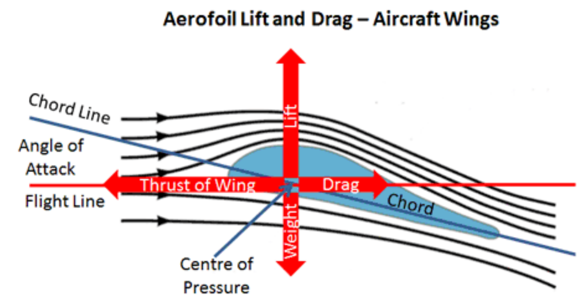
Basic concept of digital design and design optimization: design can be numerated, and compared numerically.

Selecting the "best" design within the available means

1. What is our criterion for "best" design?	**Objective function**
2. What are the available means?	**Constraints (design requirements)**
3. How do we describe different designs?	**Design Variables**

Lecture 4: Digital Design for AM and generative design

Design variable as the input variable



For computational design optimization,

⇨ **Objective function and constraints must be expressed as a function of design variables (or design vector X)**

Objective function: $f(\mathbf{x})$ Constraints: $g(\mathbf{x})$, $h(\mathbf{x})$

Cost = f(design)

Lift = f(design)

Drag = f(design)

Mass = f(design)

What is "f" for each case?

Lecture 4: Digital Design for AM and generative design

Optimization statement

$$\begin{aligned} &\text{Minimize} \quad f(\mathbf{x}) \\ &\textit{Subject to} \quad g(\mathbf{x}) \le 0 \\ &\qquad\qquad\quad\; h(\mathbf{x}) = 0 \end{aligned}$$

$f(\mathbf{x})$: **Objective function to be minimized**

$g(\mathbf{x})$: **Inequality constraints**

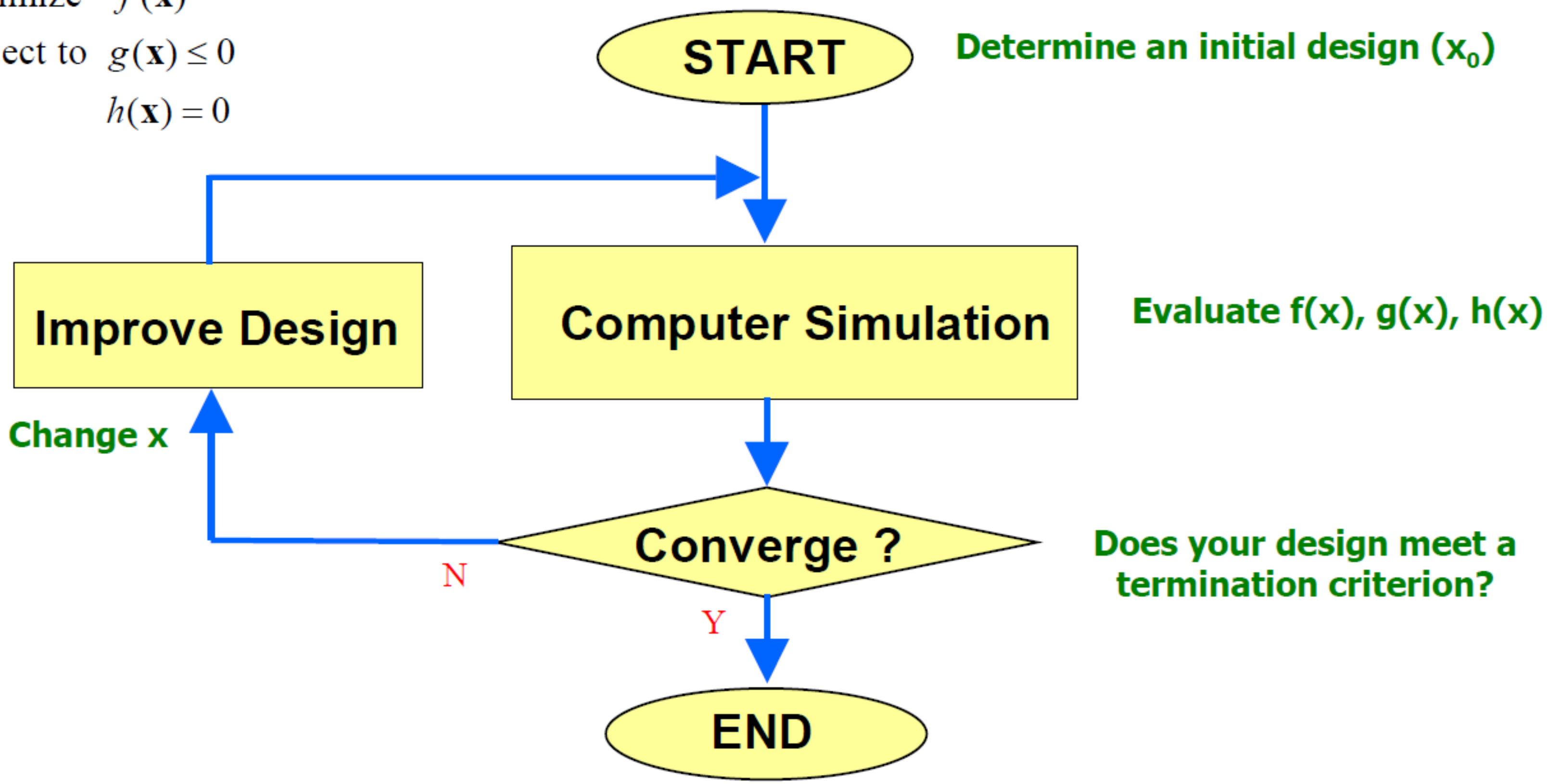
$h(\mathbf{x})$: **Equality constraints**

$\mathbf{x}$: **Design variables**

Lecture 4: Digital Design for AM and generative design

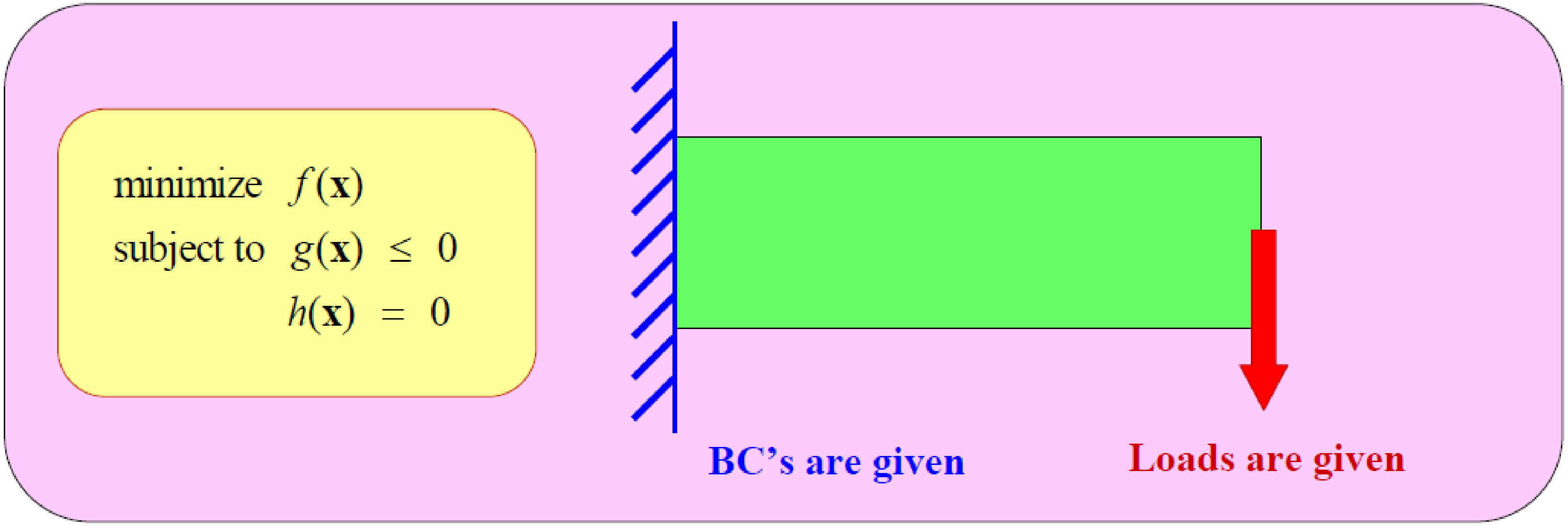
Optimization procedure

$$\begin{aligned}&\text{Minimize} \quad f(\mathbf{x})\\&\text{Subject to} \quad g(\mathbf{x}) \le 0\\&\qquad\qquad\quad h(\mathbf{x}) = 0\end{aligned}$$



Lecture 4: Digital Design for AM and generative design

Design Optimization



1. To make the structure strong
   e.g. Minimize displacement at the tip → *Min.* $f(x)$

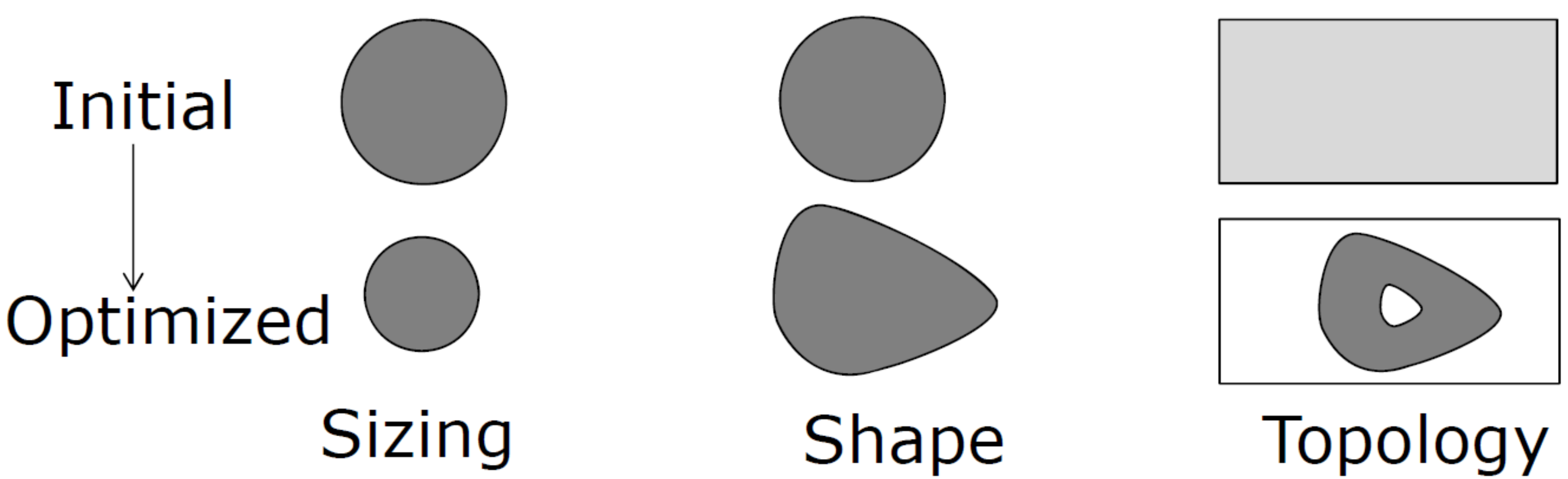
2. Total mass $\leq M_c$ → $g(x) \leq 0$

Lecture 4: Digital Design for AM and generative design

Design Optimization

Selecting the best "structural" design

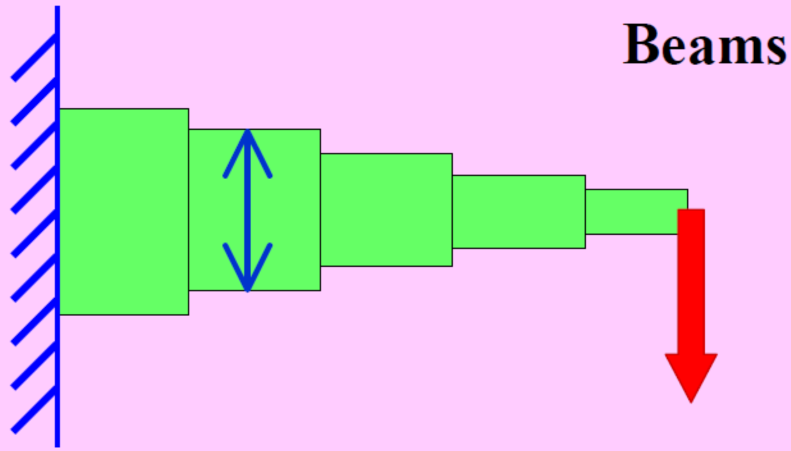
-Size Optimization
-Shape Optimization
-Topology Optimization



Lecture 4: Digital Design for AM and generative design

Size Optimization

$$
\begin{aligned}
\text{minimize} \quad & f(\mathbf{x}) \\
\text{subject to} \quad & g(\mathbf{x}) \le 0 \\
& h(\mathbf{x}) = 0
\end{aligned}
$$



Design variables (x)

x : thickness of each beam

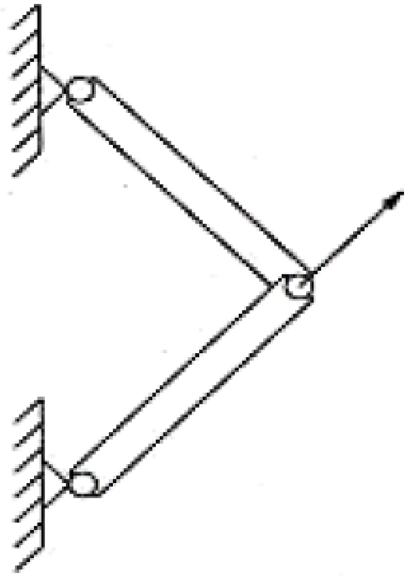
Number of design variables (ndv)

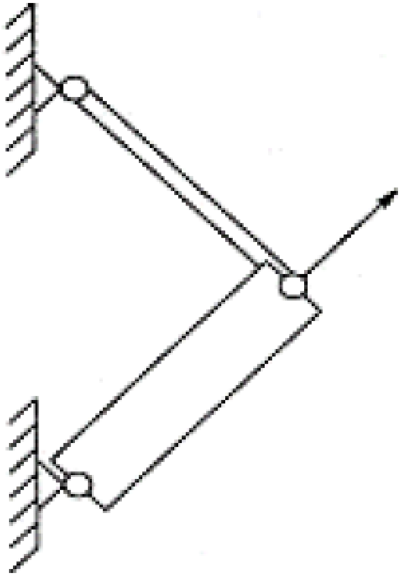
ndv = 5

***f*(x) : compliance**

***g*(x) : mass**

Lecture 4: Digital Design for AM and generative design



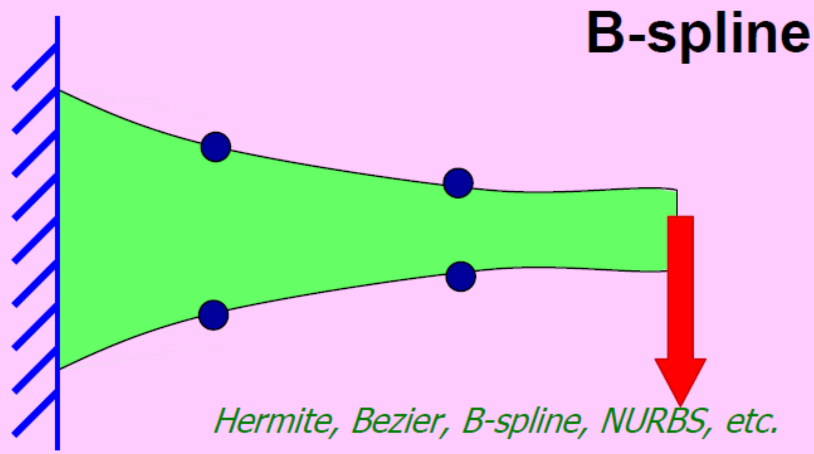


- Shape
  Topology } are given
- Optimize cross sections

Lecture 4: Digital Design for AM and generative design

Shape Optimization

$$
\begin{aligned}
\text{minimize} \quad & f(\mathbf{x}) \\
\text{subject to} \quad & g(\mathbf{x}) \le 0 \\
& h(\mathbf{x}) = 0
\end{aligned}
$$



Design variables (x)

x : control points of the B-spline

(position of each control point)

***f*(x) : compliance**

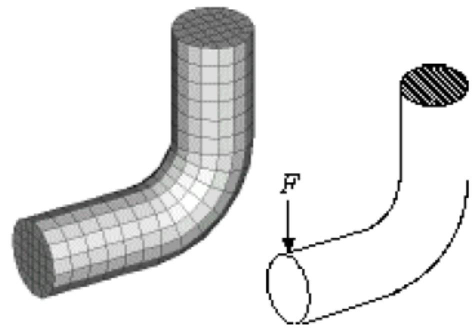
***g*(x) : mass**

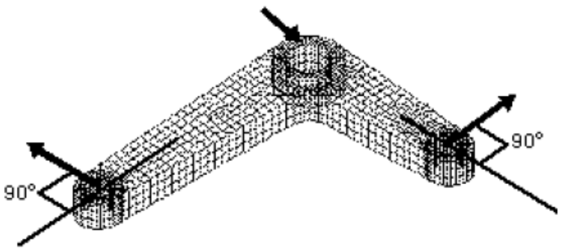
Number of design variables (ndv)

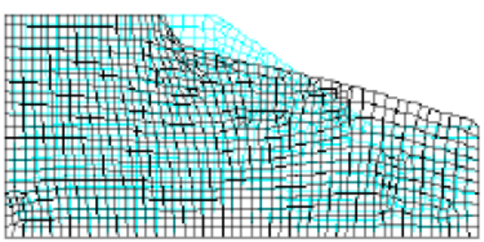
ndv = 8

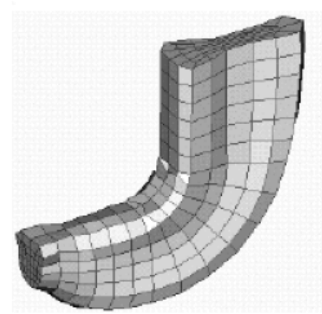
Lecture 4: Digital Design for AM and generative design

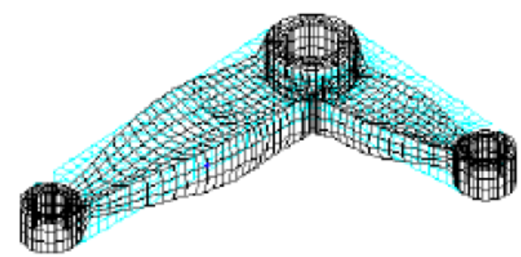
Fillet problem **Hook problem** **Arm problem**











Lecture 4: Digital Design for AM and generative design

Multiobjective & Multidisciplinary Shape Optimization

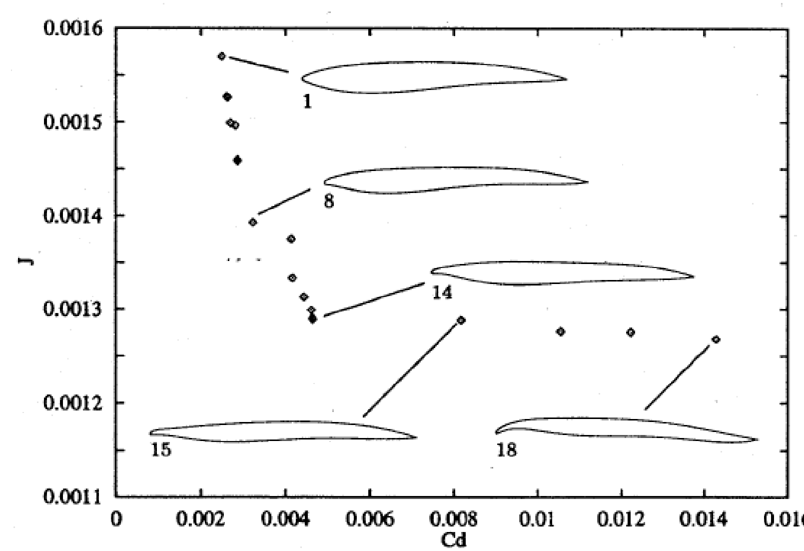
Objective function

1. Drag coefficient,   2. Amplitude of backscattered wave

Analysis

1. Computational Fluid Dynamics Analysis
2. Computational Electromagnetic Wave Field Analysis

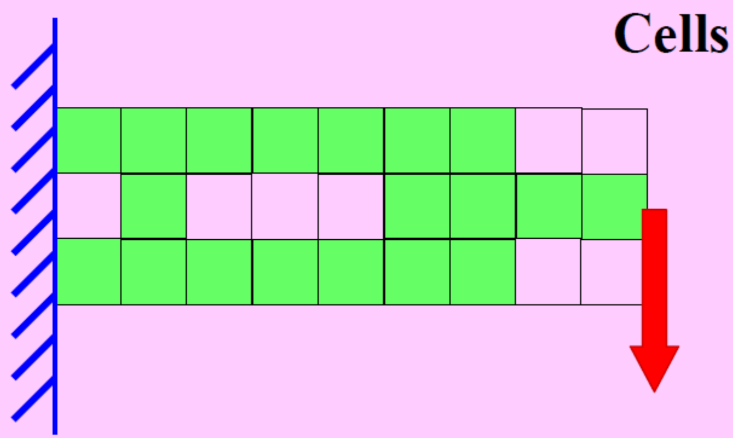
Obtain Pareto Front



Lecture 4: Digital Design for AM and generative design

Topology Optimization

$$
\begin{aligned}
\text{minimize} \quad & f(\mathbf{x}) \\
\text{subject to} \quad & g(\mathbf{x}) \leq 0 \\
& h(\mathbf{x}) = 0
\end{aligned}
$$



Design variables (x)

x : density of each cell

Number of design variables (ndv)

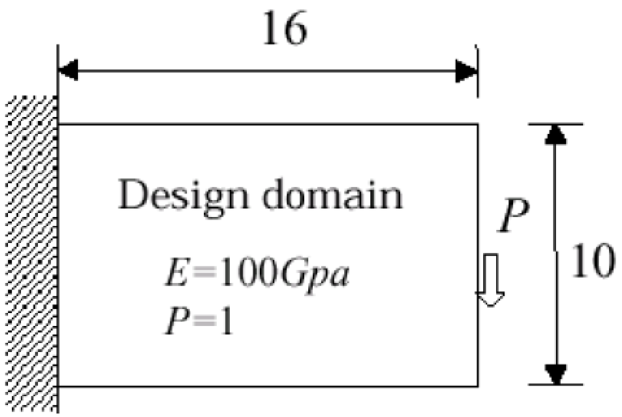
ndv = 27

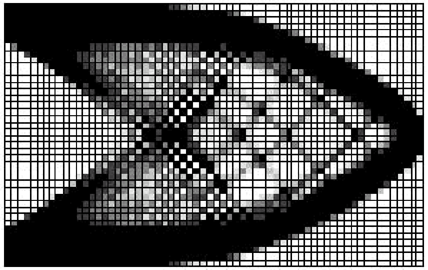
***f*(x) : compliance**

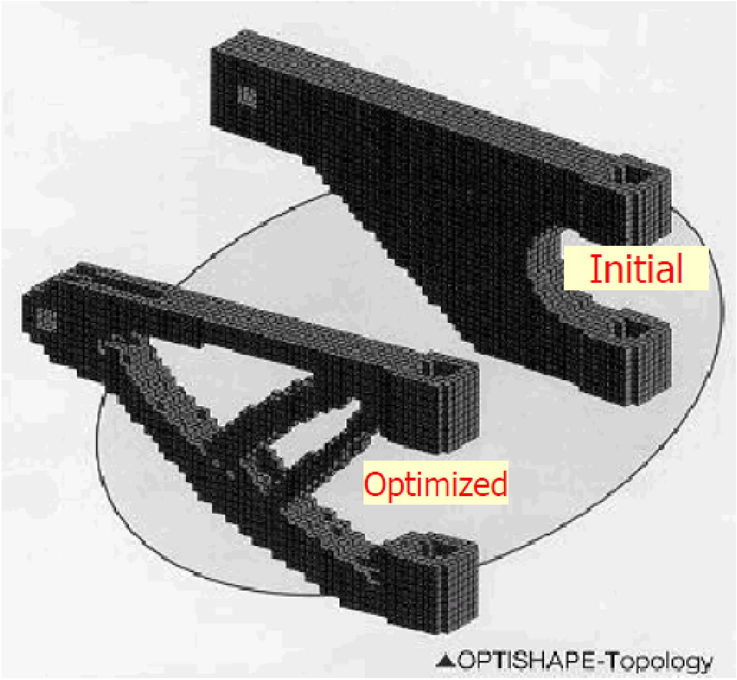
***g*(x) : mass**

Lecture 4: Digital Design for AM and generative design

Short Cantilever problem







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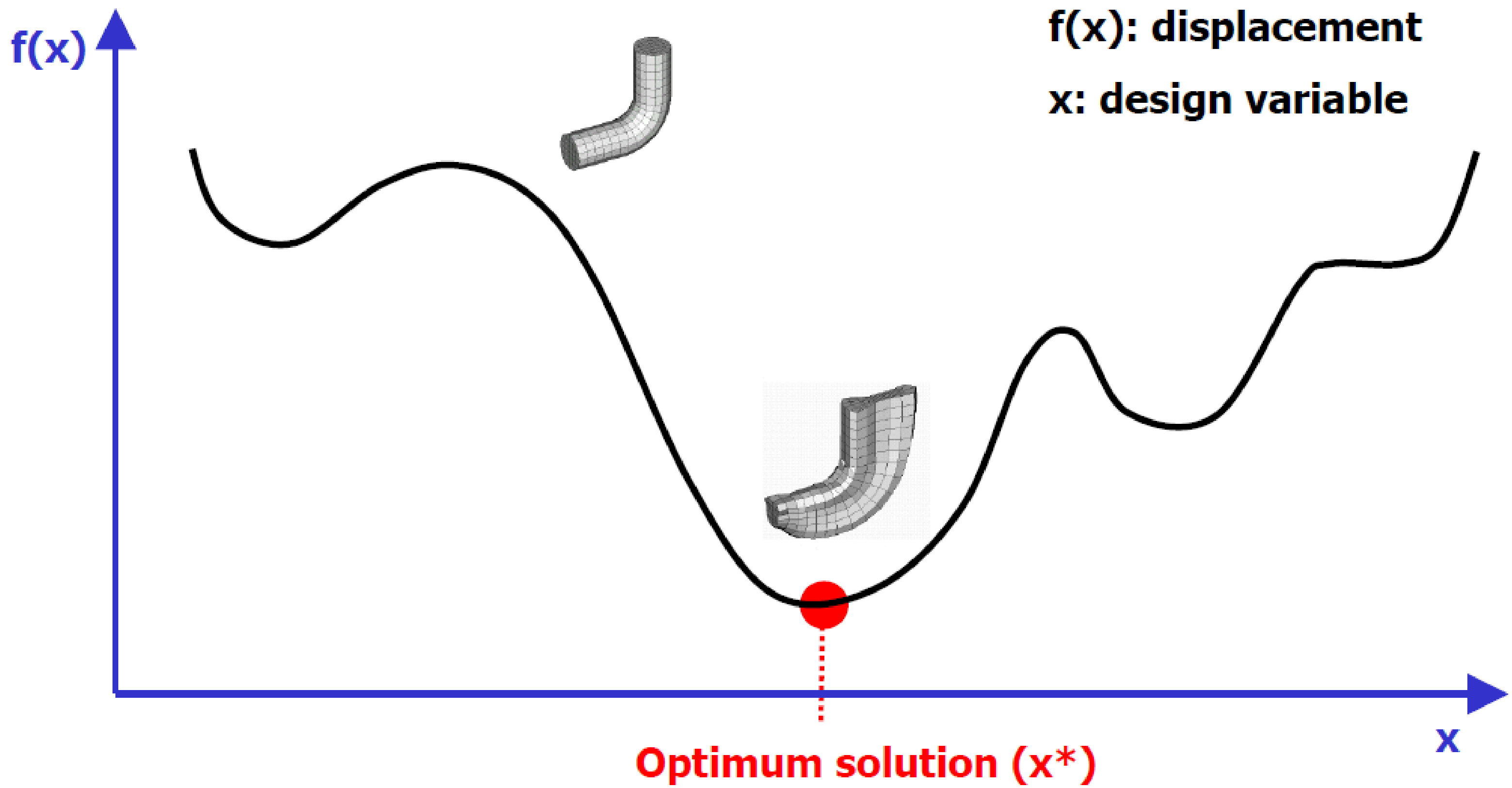
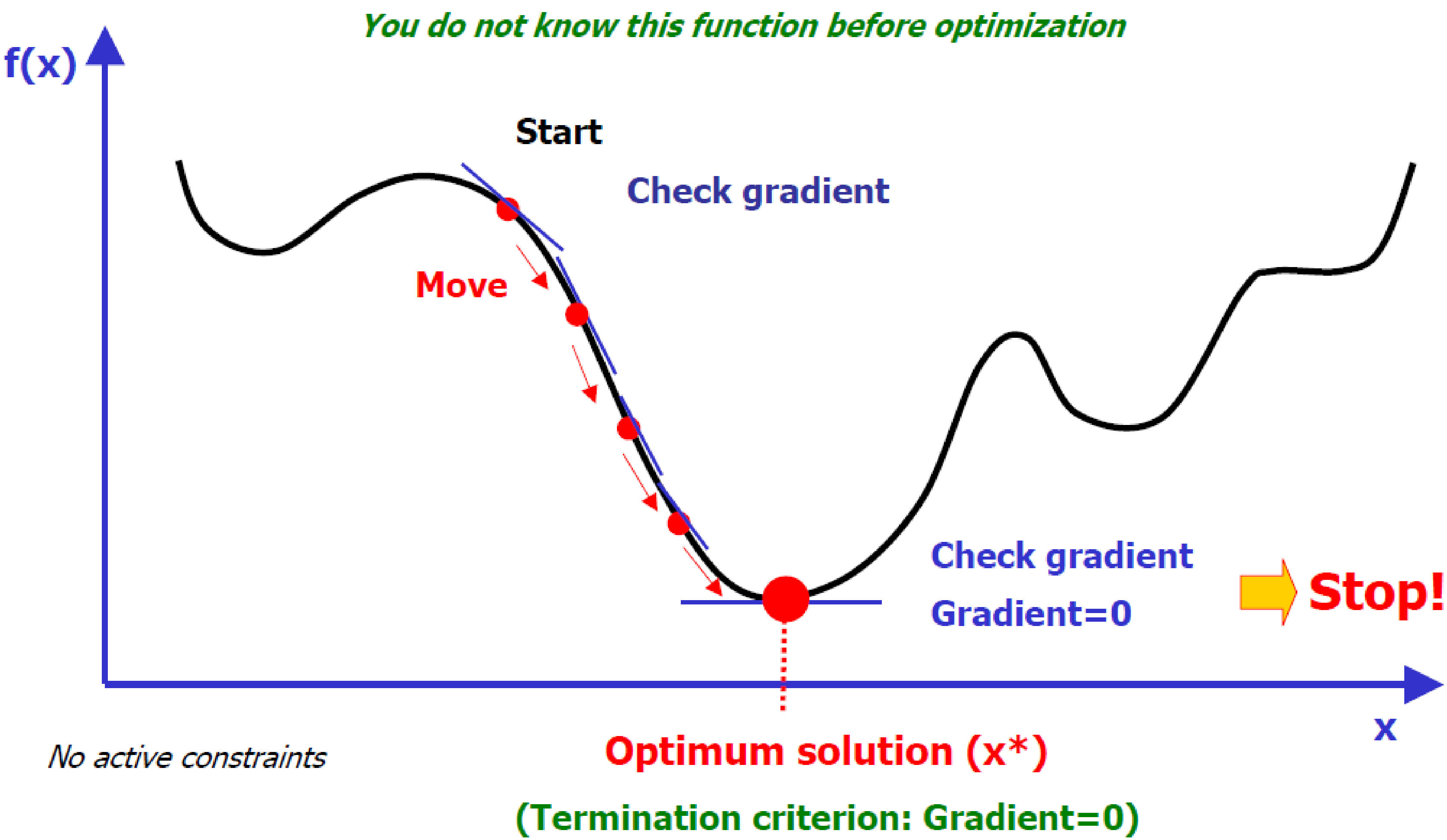
Optimum solution with graphic representation



Lecture 4: Digital Design for AM and generative design

Optimization method: Gradient-based method



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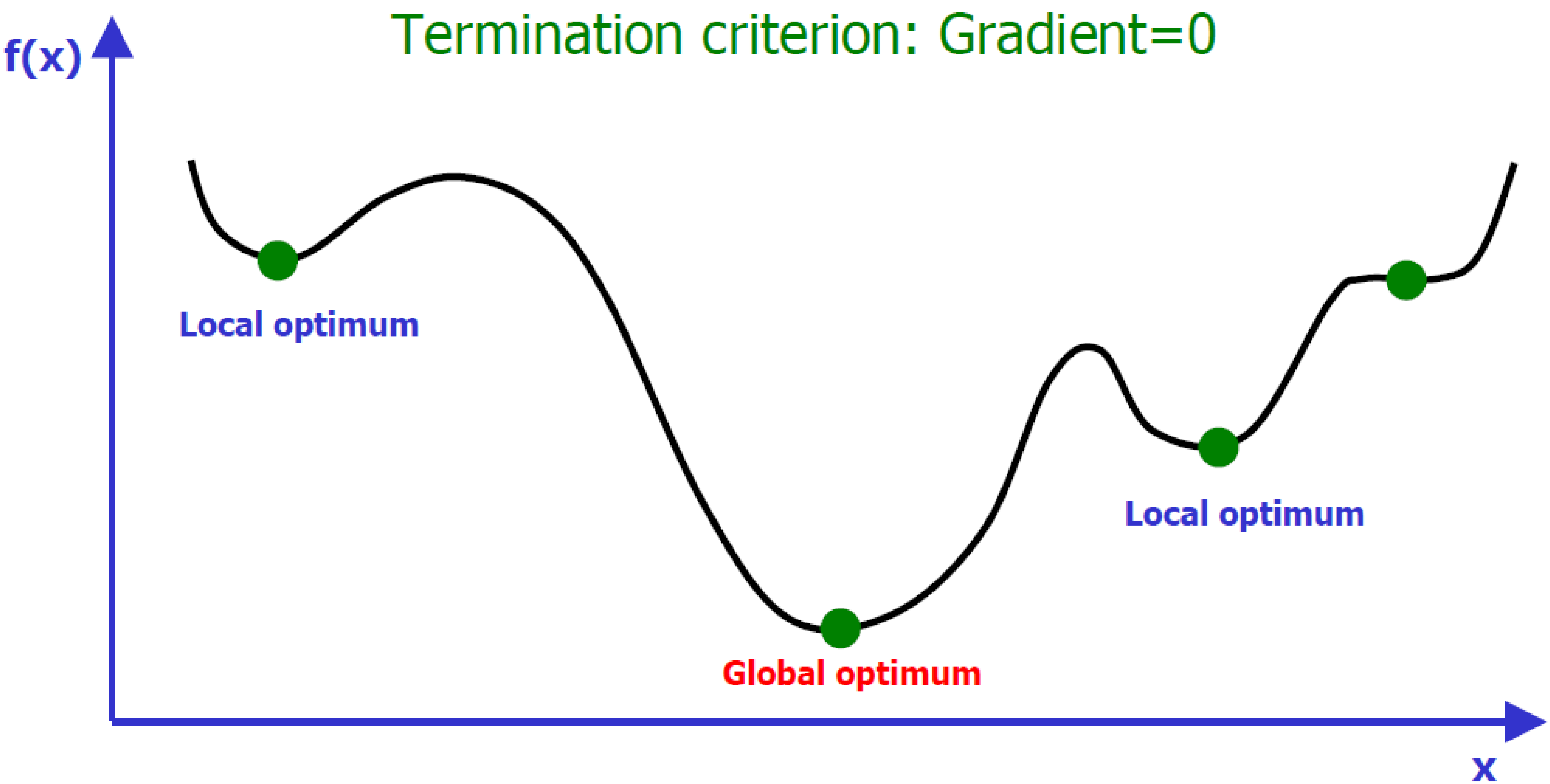
Gradient-based method, local vs global



No active constraints

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Optimization method: Gradient-based method

UNCONSTRAINED

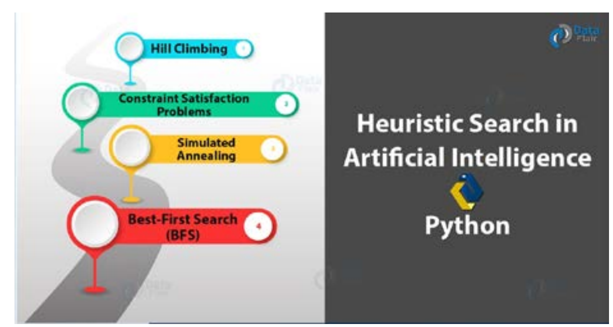
Steepest Descent
Conjugate Gradient
Quasi-Newton
Newton

CONSTRAINED

Simplex – linear
SLP – linear
SQP – nonlinear, expensive, common in engineering applications
Exterior Penalty – nonlinear, discontinuous design spaces
Interior Penalty – nonlinear
Generalized Reduced Gradient – nonlinear
Method of Feasible Directions – nonlinear
Mixed Integer Programming

Optimization method: Heuristic method

- Heuristics Often Incorporate Randomization
- **3 Most Common Heuristic Techniques**
  - Genetic Algorithms
  - Simulated Annealing
  - Tabu Search



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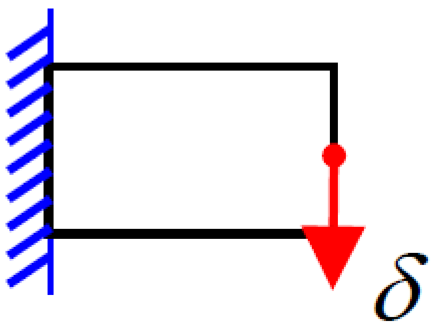
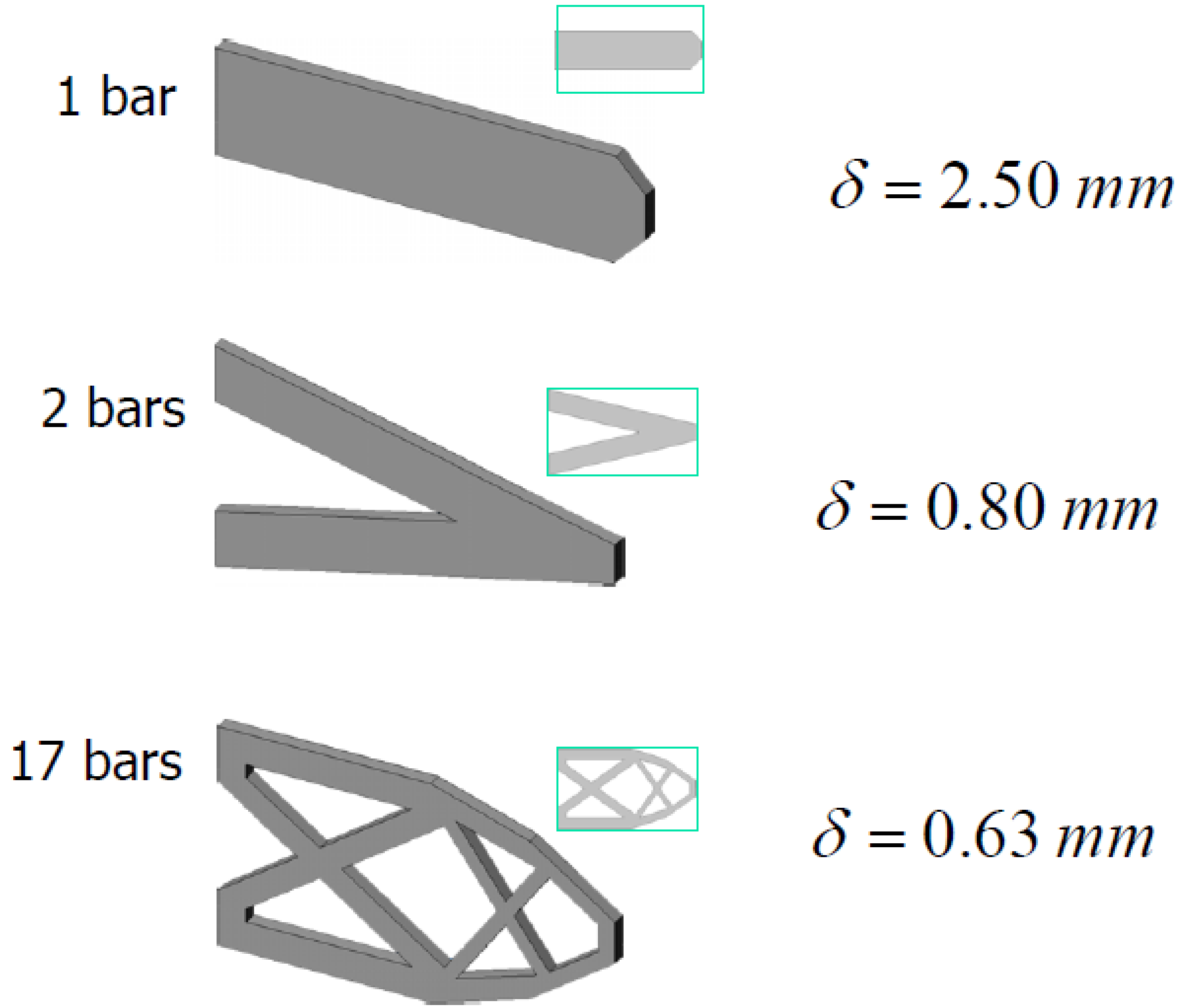
Design freedom



Volume is the same.



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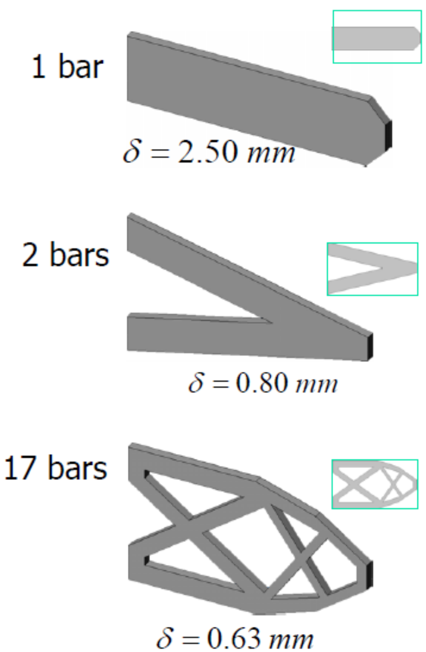
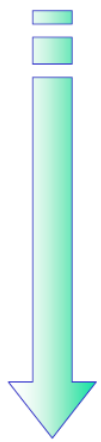
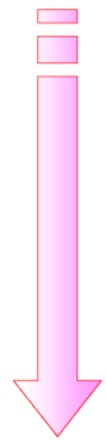
Cost vs Performance





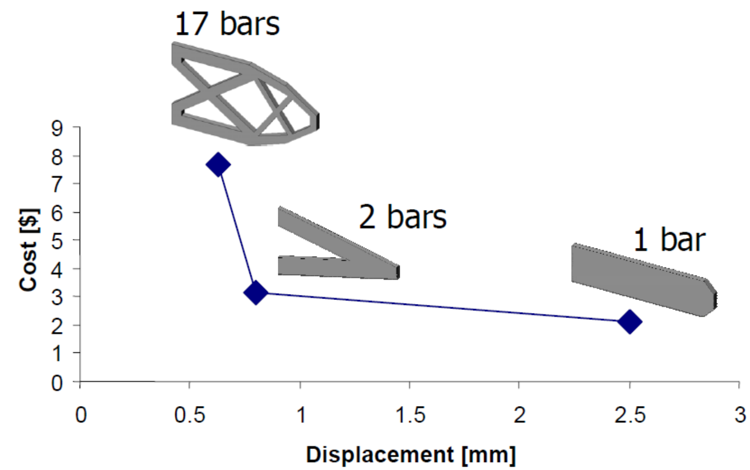
More design freedom

(Better performance)



More complex

(More difficult to optimize)



Thank you for your attention