

Multidisciplinary System Design Optimization (MSDO)

Problem Formulation

Lecture 2

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- MDO definition
- Optimization problem formulation
- MDO in the design process
- MDO challenges

What is MDO ?

- A methodology for the design of complex engineering systems and subsystems that coherently exploits the synergism of mutually interacting phenomena
- Optimal design of complex engineering systems which requires analysis that accounts for interactions amongst the disciplines (= parts of the system)
- “How to decide what to change, and to what extent to change it, when everything influences everything else.”

Ref: AIAA MDO website <http://www.aiaa.org> (Click Inside AIAA, Technical Committees)

Aircraft:

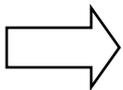
Aerodynamics
Propulsion
Structures
Controls
Avionics/Software
Manufacturing
others

Spacecraft:

Astrodynamics
Thermodynamics
Communications
Payload & Sensor
Structures
Optics
Guidance & Control

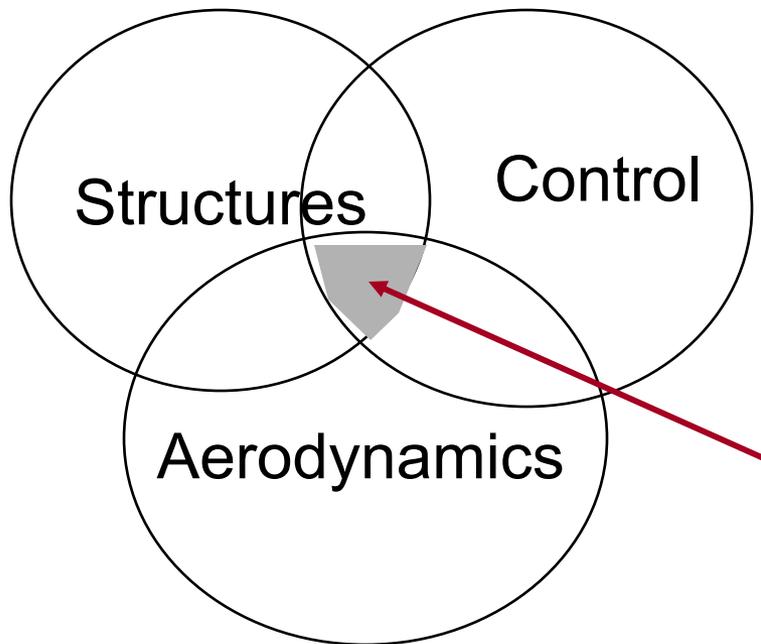
Automobiles:

Engines
Body/chassis
Aerodynamics
Electronics
Hydraulics
Industrial design
others



Fairly mature, but advances in theory, methodology, computation and application foster substantial payoffs

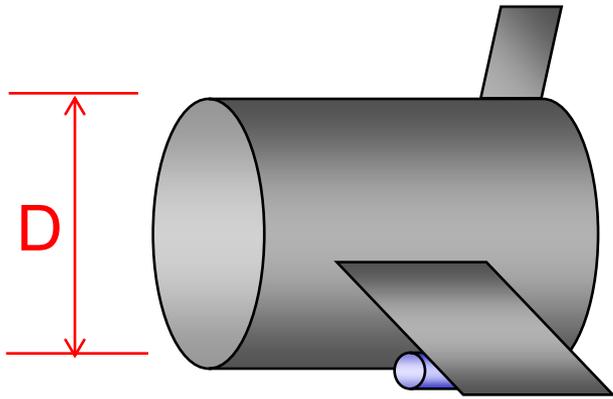
Emphasis is on the multidisciplinary nature of the complex engineering systems design process. Aerospace vehicles are a particular class of such systems.



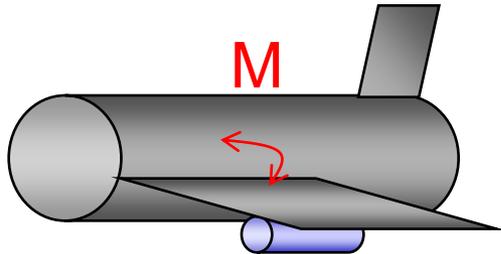
Emphasis in recent years has been on advances that can be achieved due to the interaction of two or more disciplines.

Why system-level, multidisciplinary optimization ?

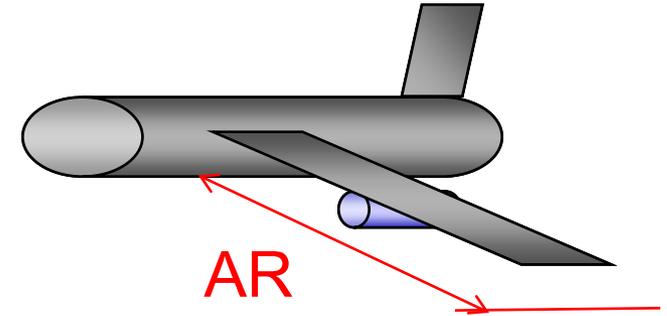
- Disciplinary specialists tend to strive towards improvement of objectives and satisfaction of constraints in terms of the variables of their own discipline
- In doing so they generate side effects - often unknowingly- that other disciplines have to absorb, usually to the detriment of the overall system performance



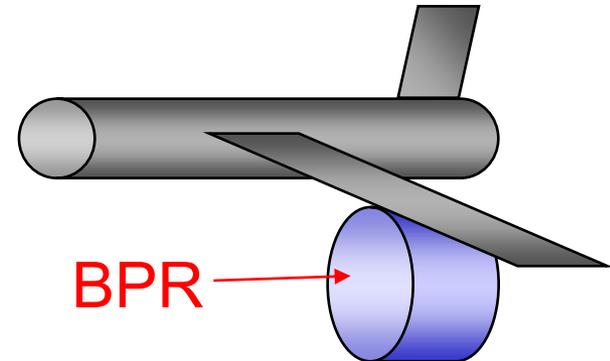
Marketing: maximize
passenger volume
→ Cabin diameter



Structures: minimize
structural mass
→ Wing-root moment



Aero: maximize L/D
→ Aspect Ratio



Propulsion: minimize
specific fuel consumption
(SFC) → Bypass Ratio

Bréguet
Range
Equation

The diagram shows the Bréguet Range Equation with arrows indicating the influence of different disciplines on its variables:

- Marketing** (red text) has arrows pointing to V and L/D .
- Aero** (red text) has an arrow pointing to L/D .
- Propulsion** (red text) has an arrow pointing to SFC .
- Structures** (red text) has an arrow pointing to W_{final} .
- All** (orange text) has an arrow pointing to the entire equation.

$$R = \frac{V(L/D)}{g \cdot SFC} \cdot \ln \frac{W_{initial}}{W_{final}}$$

R = Range [m]

V = Flight velocity [m/s]

SFC = Specific Fuel Consumption [kg/s/N]

L/D = Lift-over-Drag ration [N/N]

g = gravitational acceleration [m/s^2]

$W_{initial}$ = Initial (takeoff) weight [N]

W_{final} = Weight at end of flight [N]

$W_{fuel} = W_{initial} - W_{final}$ Fuel quantity [N]

It is wrong to think of MDO as “automated” or “push-button” design:

- The human strengths (creativity, intuition, decision-making) and computer strengths (memory, speed, objectivity) should complement each other
- The human will always be the Meta-designer
- Challenges of defining an effective interface – continuous vs. discrete thinking
- Challenges of visualization in multidimensional space, e.g. search path from initial design to final design



Human element is a key component in any successful system design methodology

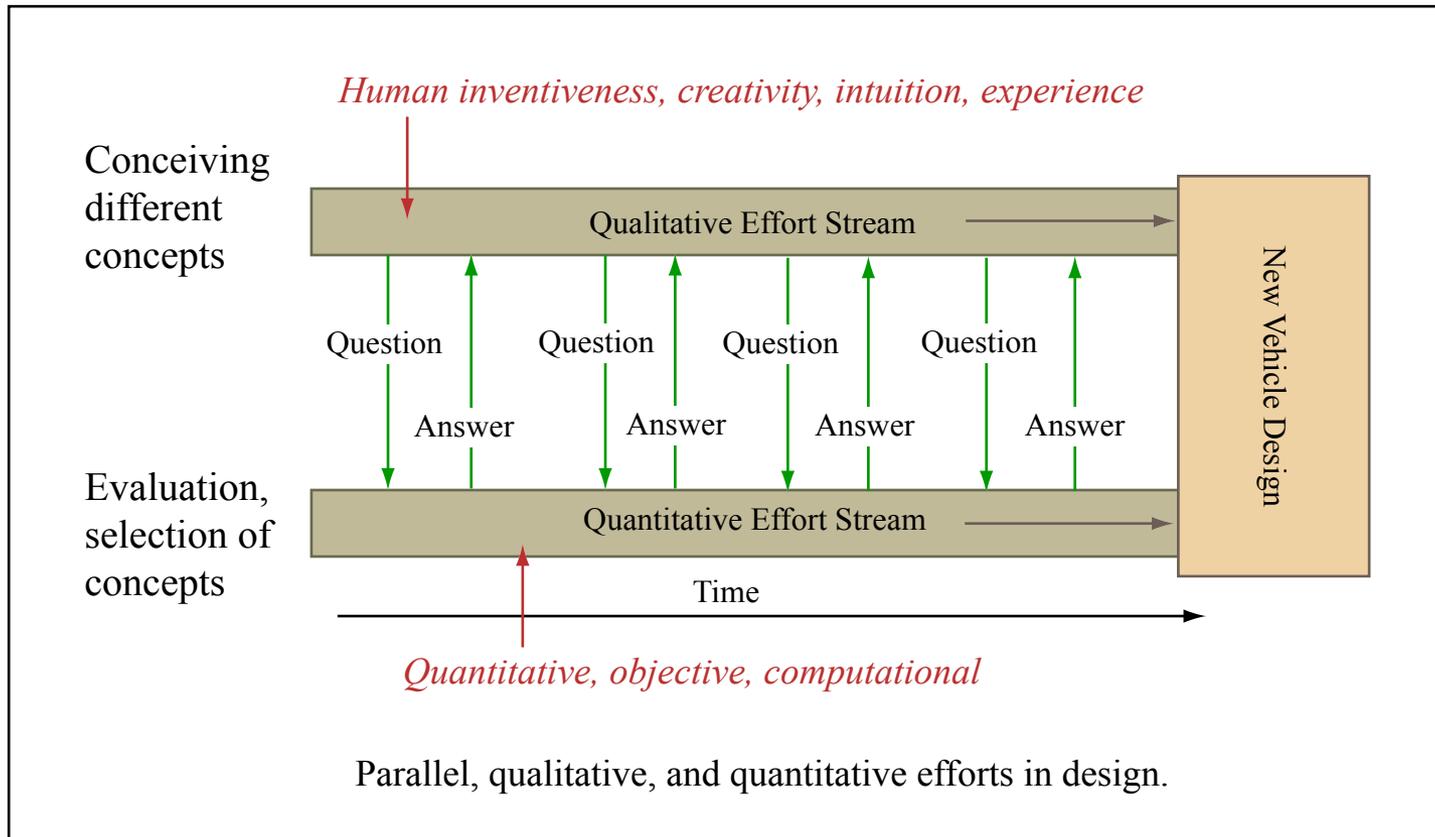


Image by MIT OpenCourseWare.

Human mind is the driving force in the design process. MDO is a way of formalizing the quantitative tool to apply the best trade-offs.

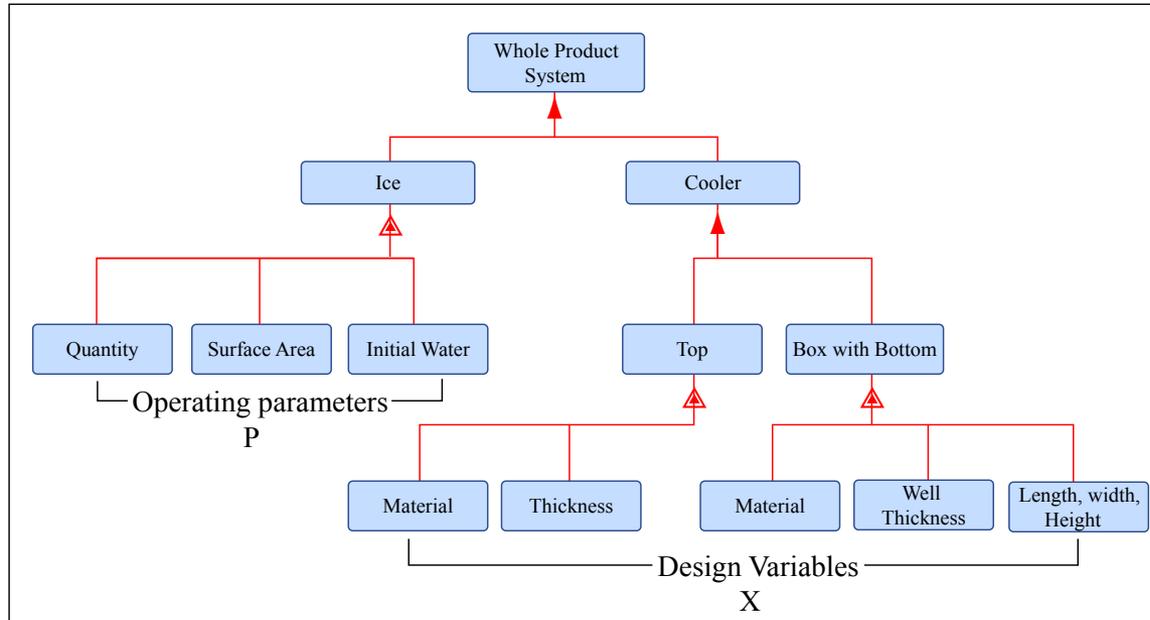
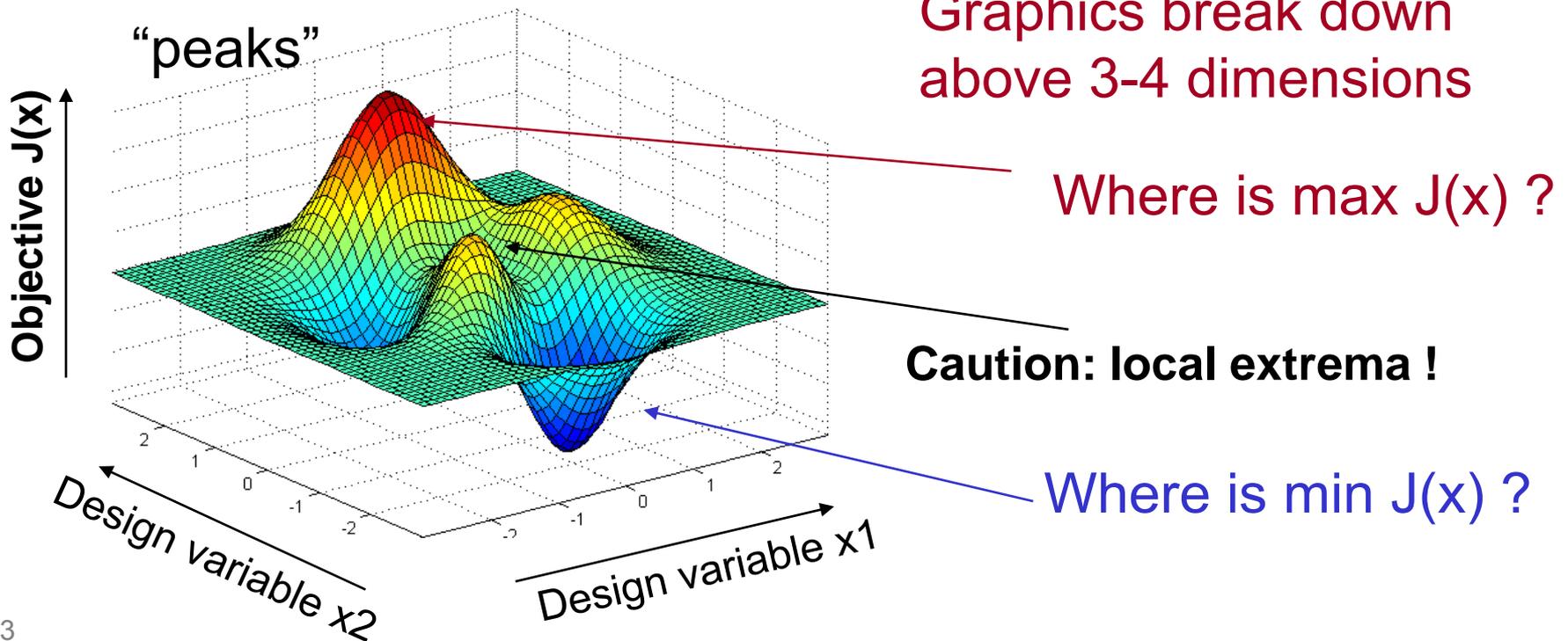


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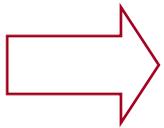
- Architecture selects the concept, decomposition and mapping of form to function
- Architecture establishes the vector of design and operating parameters
- Design selects the values of the vector of variables
- This is what optimization is good for
- Some work in “architecture” is just an exhaustive search over the design of one architecture

Optimization Problem Formulation

- Optimization methods have been combined with design synthesis and parametric analysis for ca. 40 years
- Traditionally used graphical methods to find maximum or minimum of a multivariate function (“carpet plot”), but....



- Any design can be defined by a vector in multidimensional space, where each design variable represents a different dimension
- For $n > 3$ a combinatorial “explosion” takes place and the design space cannot be computed and plotted in polynomial time
- Numerical optimization offers an alternative to the graphical approach and “brute force” evaluation



During past three decades much progress has been made in numerical optimization

Quantitative side of the design problem may be formulated as a problem of Nonlinear Programming (NLP)

$$\min_{\mathbf{x}, \mathbf{p}} \mathbf{J}$$

$$\text{s.t. } \mathbf{g}(\mathbf{x}, \mathbf{p}) \leq 0$$

$$\mathbf{h}(\mathbf{x}, \mathbf{p}) = 0$$

$$x_{i, LB} \leq x_i \leq x_{i, UB} \quad (i = 1, \dots, n)$$

This is the problem formulation that we will discuss this semester.

$$\text{where } \mathbf{J} = \begin{bmatrix} J_1 & \mathbf{x} & \cdots & J_z & \mathbf{x} \end{bmatrix}^T$$

$$\mathbf{x} = \begin{bmatrix} x_1 & \cdots & x_i & \cdots & x_n \end{bmatrix}^T$$

$$\mathbf{g} = \begin{bmatrix} g_1(\mathbf{x}) & \cdots & g_{m_1}(\mathbf{x}) \end{bmatrix}^T$$

$$\mathbf{h} = \begin{bmatrix} h_1(\mathbf{x}) & \cdots & h_{m_2}(\mathbf{x}) \end{bmatrix}^T$$

The objective can be a vector \mathbf{J} of z system responses or characteristics we are trying to maximize or minimize

$$\mathbf{J} = \begin{bmatrix} J_1 \\ J_2 \\ J_3 \\ J_i \\ \vdots \\ J_z \end{bmatrix} = \begin{bmatrix} \text{cost} \quad [\$] \\ \text{range} \quad [\text{km}] \\ \text{weight} \quad [\text{kg}] \\ \text{data rate} \quad [\text{bps}] \\ \vdots \\ \text{ROI} \quad [\%] \end{bmatrix}$$

Often the objective is a scalar function, but for real systems often we attempt multi-objective optimization:

$$\mathbf{x} \mapsto \mathbf{J}(\mathbf{x})$$

Some objectives can be conflicting.

Design vector \mathbf{x} contains n variables that form the design space

During design space exploration or optimization we change the entries of \mathbf{x} in some rational fashion to achieve a desired effect

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_i \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} \text{aspect ratio [-]} \\ \text{transmit power [W]} \\ \text{\# of apertures [-]} \\ \text{orbital altitude [km]} \\ \vdots \\ \text{control gain [V/V]} \end{bmatrix}$$

x_i can be

Real: $x_i \in \mathcal{R}$

Integer: $x_i \in \mathcal{I}$

Binary: $x_i \in \{0, 1\}$

Boolean: $x_i \in \{\text{true}, \text{false}\}$



Design variables are “controlled” by the designers

Parameters p are quantities that affect the objective J , but are considered fixed, i.e. they cannot be changed by the designers.

Sometimes parameters p can be turned into design variables x_i to enlarge the design space.

Sometimes parameters p are former design variables that were fixed at some value because they were found not to affect any of the objectives J_i or because their optimal level was predetermined.

Constraints act as boundaries of the design space \mathbf{x} and typically occur due to finiteness of resources or technological limitations of some design variables.

Often, but not always, optimal designs lie at the intersection of several active constraints

Inequality constraints: $g_j \mathbf{x} \leq 0 \quad j = 1, 2, \dots, m_1$

Equality constraints: $h_k \mathbf{x} = 0 \quad k = 1, 2, \dots, m_2$

Bounds: $x_{i,LB} \leq x_i \leq x_{i,UB} \quad i = 1, 2, \dots, n$



Objectives are what we are trying to achieve
Constraints are what we cannot violate
Design variables are what we can change

It can be difficult to choose whether a condition is a constraint or an objective.

For example: should we try to minimize cost, or should we set a constraint stating that cost should not exceed a given level.

The two approaches can lead to different designs.

Sometimes, the initial formulation will need to be revised in order to fully understand the design space.

In some formulations, all constraints are treated as objectives (physical programming).

design variables

objective function

Minimize the **take-off weight of the aircraft** by changing **wing geometric parameters** while satisfying the given **range and payload requirements** at the given **cruise speed**.

constraints

parameter

For your group's system:

1. Consider the preliminary design phase.

Identify:

- important disciplines
- potential objective functions
- potential design variables
- system parameters
- constraints and bounds

2. Report out

MDO in the Design Process

MDO mathematically traces a path in the design space from some initial design \mathbf{x}_0 towards improved designs (with respect to the objective \mathbf{J}).

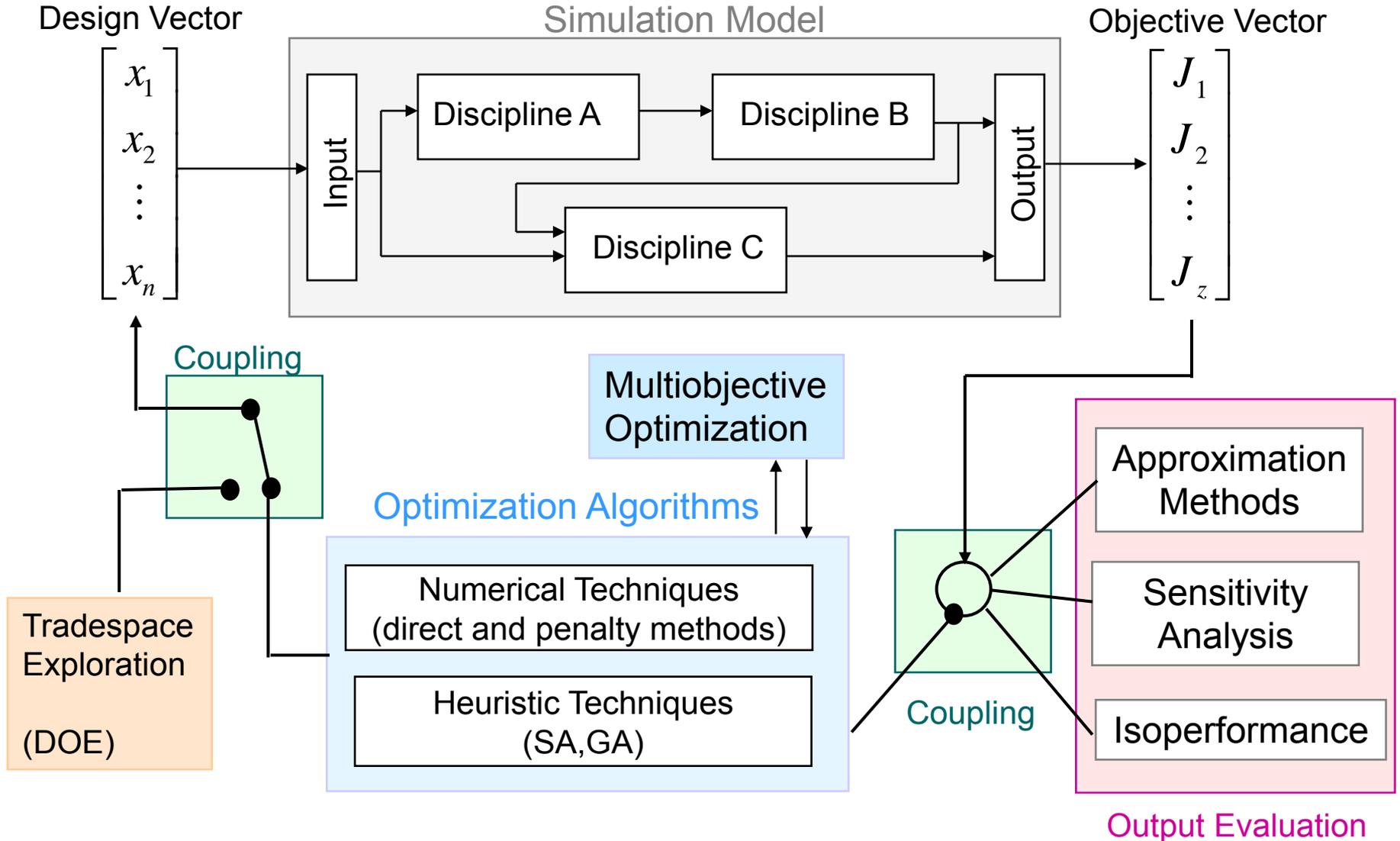
It does this by operating on a large number of variables and functions simultaneously - a feat beyond the power of the human mind.

The path is not biased by intuition or experience.

This path instead of being invisible inside a “black box” becomes more visible by various MDO techniques such as sensitivity analysis and visualization



Optimization does not remove the designer from the loop, but it helps conduct trade studies



There are two distinct components of the MSDO process:

The **optimization algorithm** decides how to move through the design space.

The **simulation model** evaluates designs chosen by the optimizer. Both objective functions and constraints must be evaluated.

Sometimes, disciplinary simulation models can be used in an optimization framework, but often they are not appropriate.

There are several different approaches to couple the optimizer and the simulation models (Lecture 4).

- (1) Define overall system requirements
- (2) Define design vector \mathbf{x} , objective \mathbf{J} and constraints
- (3) System decomposition into modules
- (4) Modeling of physics via governing equations at the module level - module execution in isolation
- (5) Model integration into an overall system simulation
- (6) Benchmarking of model with respect to a known system from past experience, if available
- (7) Design space exploration (DoE) to find sensitive and important design variables x_i
- (8) Formal optimization to find $\min J(\mathbf{x})$
- (9) Post-optimality analysis to explore sensitivity and tradeoffs: sensitivity analysis, approximation methods, isoperformance, include uncertainty

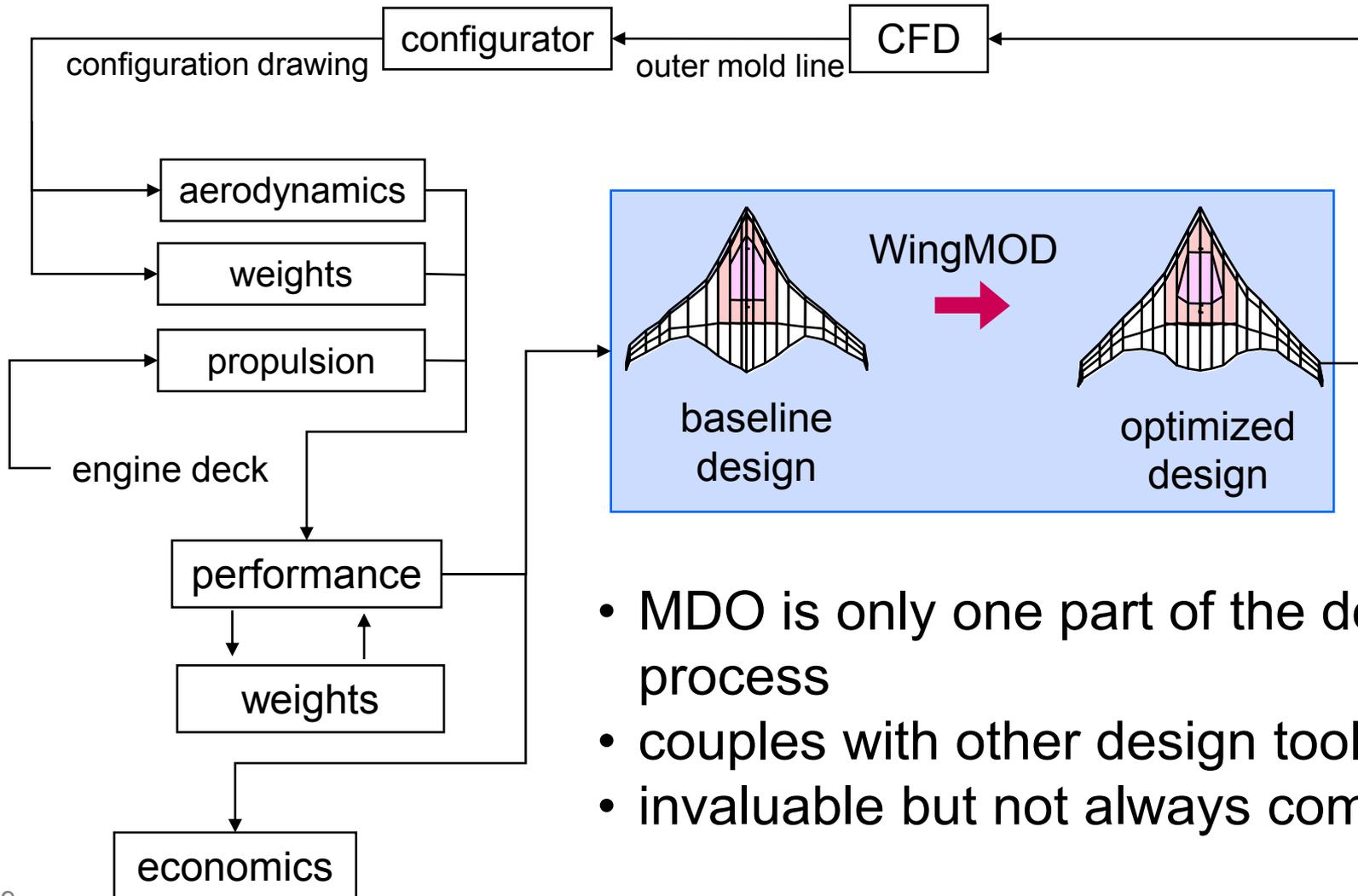
- (i) Step through (1)-(8)
- (ii) The optimizer will use an error in the problem setup to determine a mathematically valid but physically unreasonable solution

OR

The optimizer will be unable to find a feasible solution (satisfies all constraints)

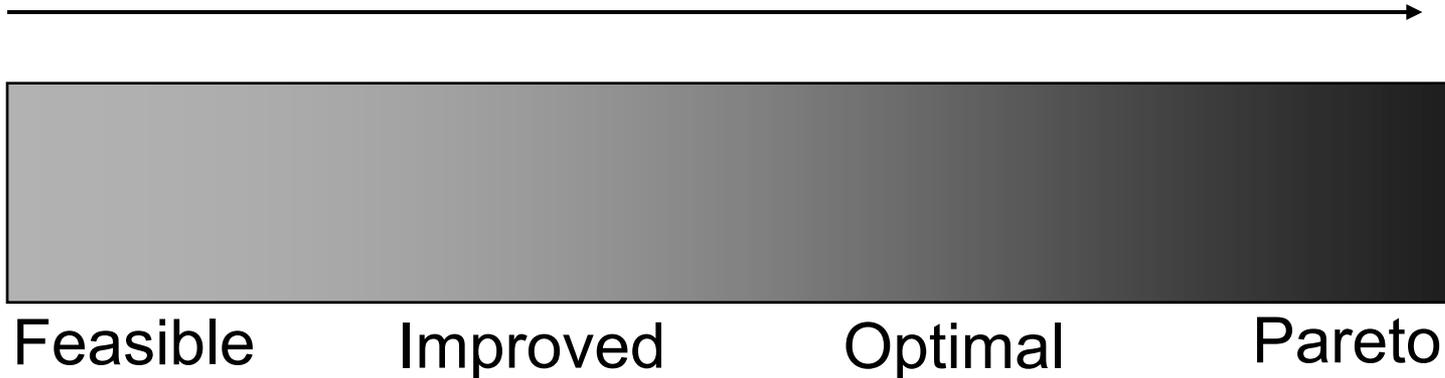
- (iii) Add, remove or modify constraints and/or design variables
- (iv) Iterate until an appropriate model is obtained

Although MDO is an automated formalization of the design process, it is a highly interactive procedure...



- The 'MD' portion of 'MDO' is important on its own
- Often MDO is used not to find the truly optimal design, but rather to find an improved design, or even a feasible design ...

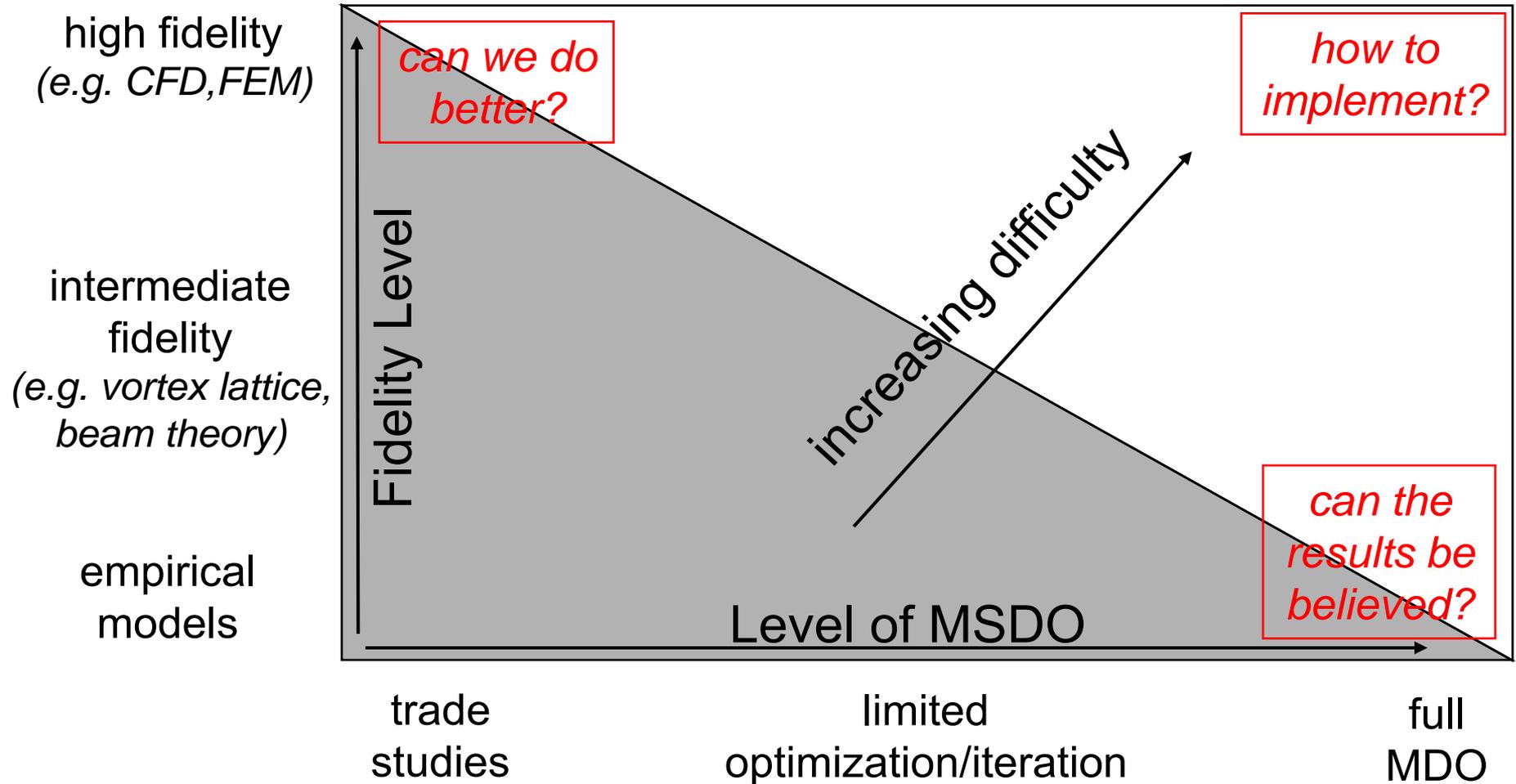
Range of design objectives

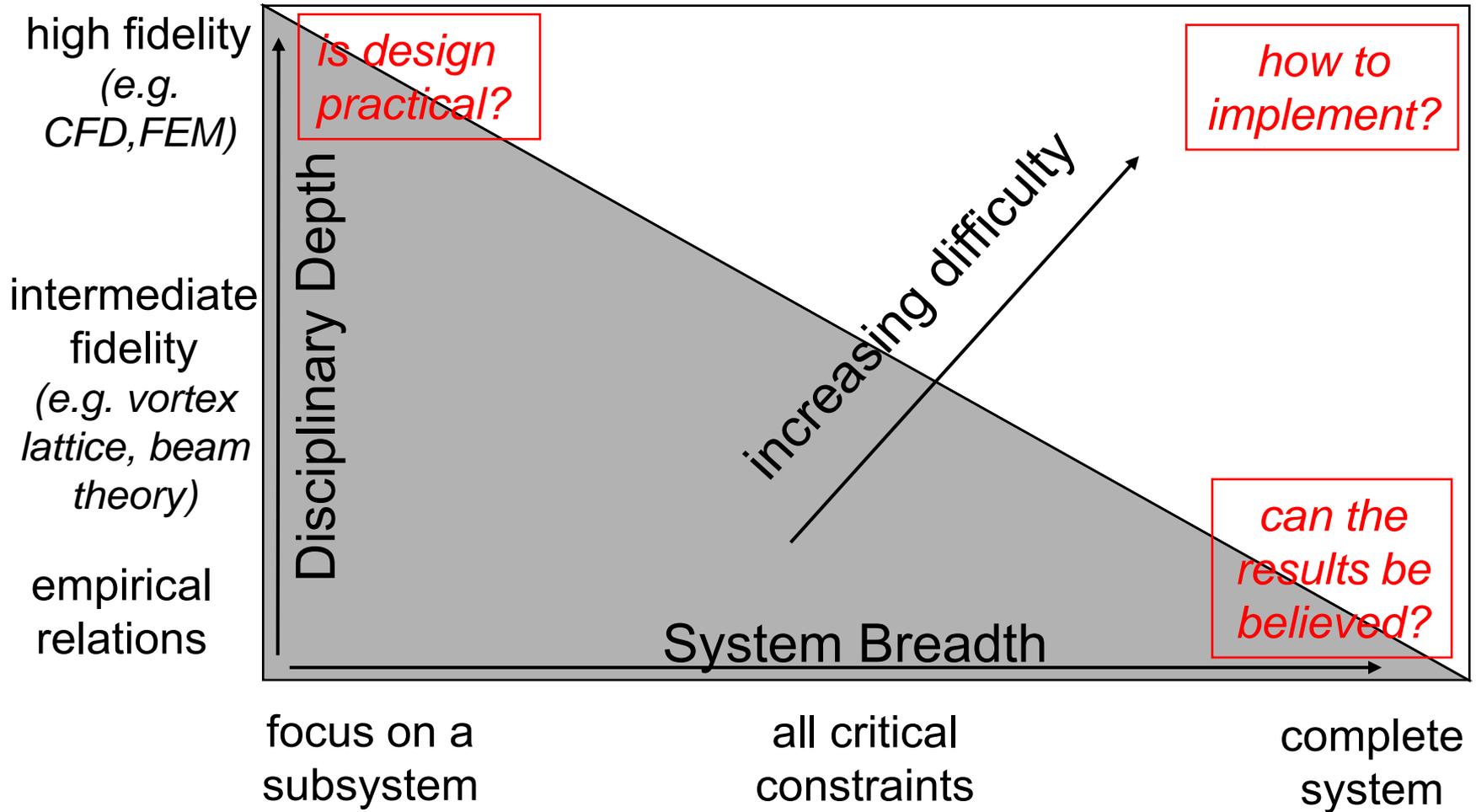


MDO Challenges

- Fidelity/expense of disciplinary models
Fidelity is often sacrificed to obtain models with short computation times.
- Complexity
Design variables, constraints and model interfaces must be managed carefully.
- Communication
The user interface is often very unfriendly and it can be difficult to change problem parameters.
- Flexibility
It is easy for an MDO tool to become very specialized and only valid for one particular problem.

How do we prevent MDO codes from becoming complex, highly specialized tools which are used by a single person (often the developer!) for a single problem?





Advantages

- reduction in design time
- systematic, logical design procedure
- handles wide variety of design variables & constraints
- not biased by intuition or experience

Disadvantages

- computational time grows rapidly with number of dv's
- numerical problems increase with number of dv's
- limited to range of applicability of analysis programs
- will take advantage of analysis errors to provide mathematical design improvements
- difficult to deal with discontinuous functions

- MDO is not a stand-alone, automated design process
- MDO is a valuable tool that requires substantial human interaction and complements other design tools
- Elements of an MDO framework
- MDO Challenges



Next two lectures will address Modeling & Simulation and Problem Decomposition

- Kroo, I.: “MDO applications in preliminary design: status and directions,” AIAA Paper 97-1408, 1997.
- Kroo, I. and Manning, V.: “Collaborative optimization: status and directions,” AIAA Paper 2000-4721, 2000.
- Sobieski, I. and Kroo, I.: “Aircraft design using collaborative optimization,” AIAA Paper 96-0715, 1996.
- Balling, R. and Wilkinson, C.: “Execution of multidisciplinary design optimization approaches on common test problems,” AIAA Paper 96-4033, 1996.
- Giesing, J. and Barthelemy, J.: “A summary of industry MDO applications and needs”, AIAA White Paper, 1998.
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