Multidisciplinary System Design Optimization (MSDO)

Multidisciplinary Design and Analysis Problem Formulation

Lecture 2

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Today's Topics

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

MDO Definition

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://endo.sandia.gov/AIAA_MDOTC/main.html

Engineering Design Disciplines

Aircraft:
- Aerodynamics
- Propulsion
- Structures
- Controls
- Avionics/Software
- Manufacturing
- others

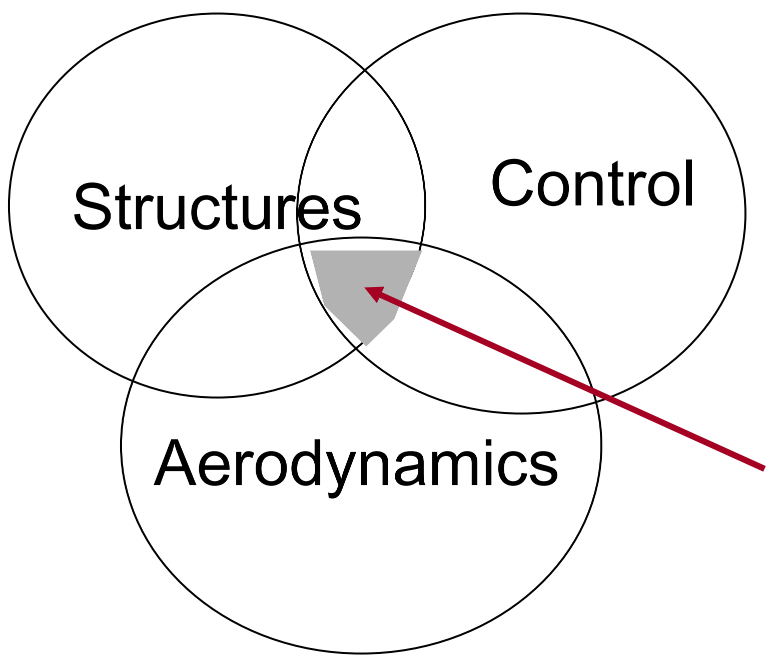
Spacecraft:
- Astrodynamics
- Thermodynamics
- Communications
- Payload & Sensor
- Structures
- Optics
- Guidance & Control

Automobiles:
- Engines
- Body/chassis
- Aerodynamics
- Electronics
- Hydraulics
- Industrial design
- others

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

Multidisciplinary Aspects of Design

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



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

System Level Optimization

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

Example: High wing aspect ratio aircraft designs

Concurrent Engineering Disciplines

Must also include the broader set of concurrent engineering (CE) disciplines.

Manufacturing:	Model manufacturing tools and processes as a function of part geometry, materials, and assemblies
Supportability:	Model parts reliability and failure rates, estimated down-time due to repairs etc...
Cost:	Estimate development, manufacturing and operations costs. Often cost-estimation relationships (CER's)

Prerequisite: Development of realistic, reliable and easy to use mathematical models for these disciplines - difficult

Supporting Disciplines

Multidisciplinary design optimization of aerospace vehicles cannot take place without substantial contributions from supporting disciplines:

- Human Interface Aspects of Design
- Intelligent and Knowledge-Based Systems
- Computing Aspects of Design
- Information Integration and Management.

Human Interface Aspects of Design

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

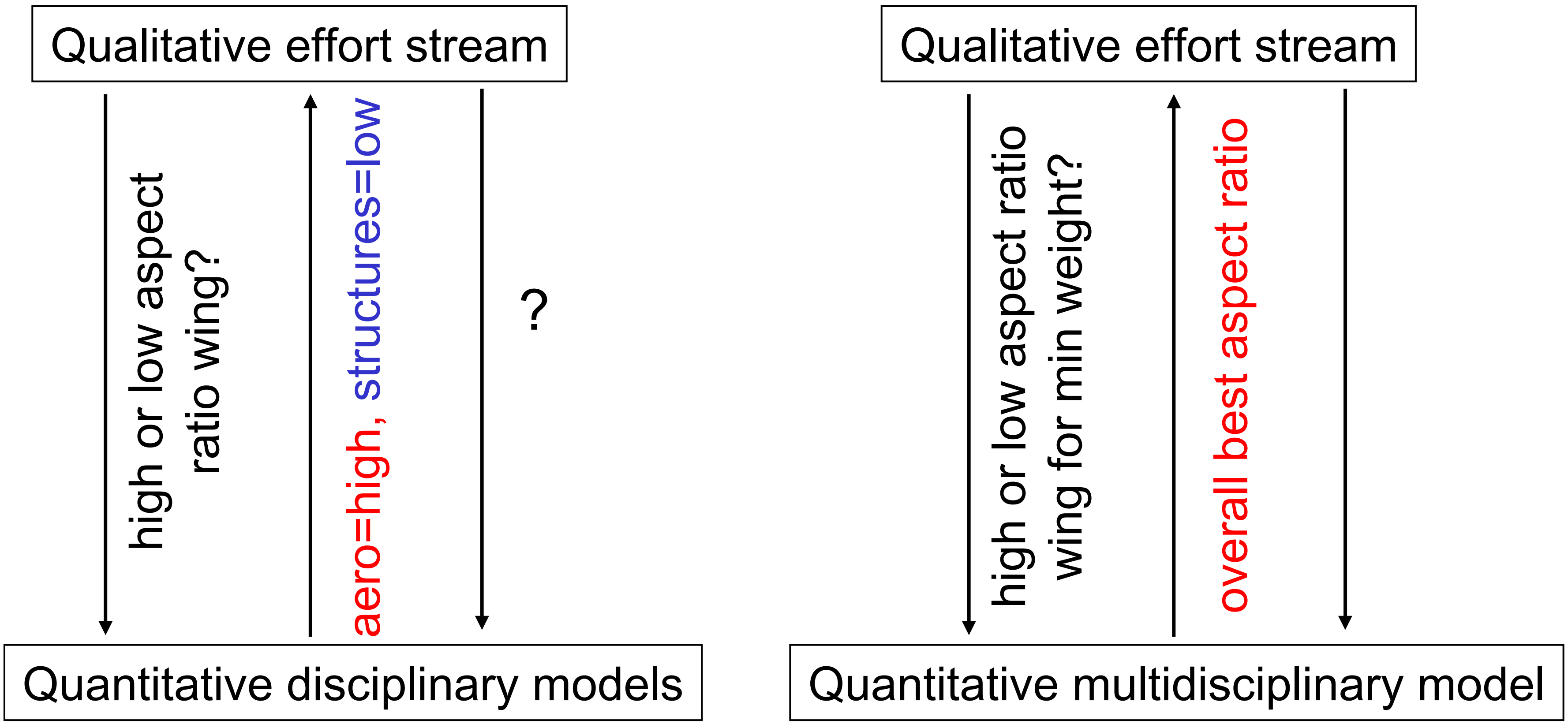
Quantitative vs. Qualitative

AIAA Technical Committee on Multidisciplinary Design Optimization (MDO).

White Paper on Current State of the Art. January 15, 1991.

Human mind is the driving force in the design process, but mathematics and computers are indispensable tools

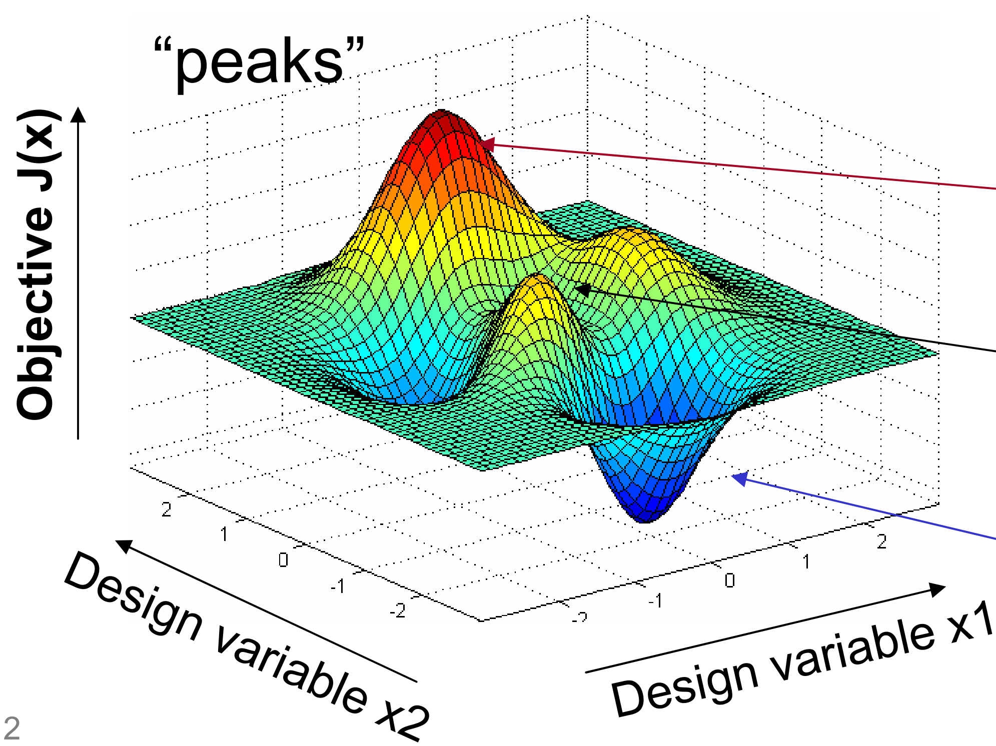
Quantitative vs. Qualitative



MDO is a way of formalizing the quantitative tool to apply the best trade-offs. The question provides a metric; the answer accounts for both disciplinary and interaction information.

Optimization Aspects of Design

- 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….



Graphics break down above 3-4 dimensions

Where is max J(x) ?

Caution: local extrema !

Where is min J(x) ?

Combinatorial Explosion

- 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

- Any design can be defined by a vector in multidimensional space, where each design variable represents a different dimension

⇨ During past two decades much progress has been made in numerical optimization

Design Variables

Design vector **x** contains *n* variables that form the design space

During design space exploration or optimization we change the entries of **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: $x_i \in \mathbb{R}$

Integer: $x_i \in \mathbb{Z}$

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

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

⇨ Design variables are "controlled" by the designers

Objectives

The objective can be a vector **J** of *z* system responses or characteristics we are trying to maximize or minimize

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

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.

Parameters

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

Constraints act as boundaries of the design space **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: $g_j(\mathbf{x}) \leq 0 \quad j = 1, 2, \ldots, m_1$

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

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

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

Constraints versus Objectives

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).

Example Problem Statement

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

Formal Notation

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

$$\min \mathbf{J}(\mathbf{x},\mathbf{p})$$
$$\text{s.t.} \quad \mathbf{g}(\mathbf{x},\mathbf{p}) \le 0$$
$$\mathbf{h}(\mathbf{x},\mathbf{p}) = 0$$
$$x_{i,LB} \le x_i \le x_{i,UB} \quad (i = 1,\ldots,n)$$

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

$$\text{where} \quad \mathbf{J} = \begin{bmatrix} J_1(\mathbf{x}) & \cdots & J_z(\mathbf{x}) \end{bmatrix}^T$$
$$\mathbf{x} = \begin{bmatrix} x_1 & \cdots & x_i & \cdots & x_n \end{bmatrix}^T$$
$$\mathbf{g} = \begin{bmatrix} g_1(\mathbf{x}) \cdots g_{m_1}(\mathbf{x}) \end{bmatrix}^T$$
$$\mathbf{h} = \begin{bmatrix} h_1(\mathbf{x}) \cdots h_{m_2}(\mathbf{x}) \end{bmatrix}^T$$

Group Exercise...

Identify five complex engineering systems:

1.
2.
3.
4.
5.

Consider the preliminary design phase.
Identify:

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

What MDO really does

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

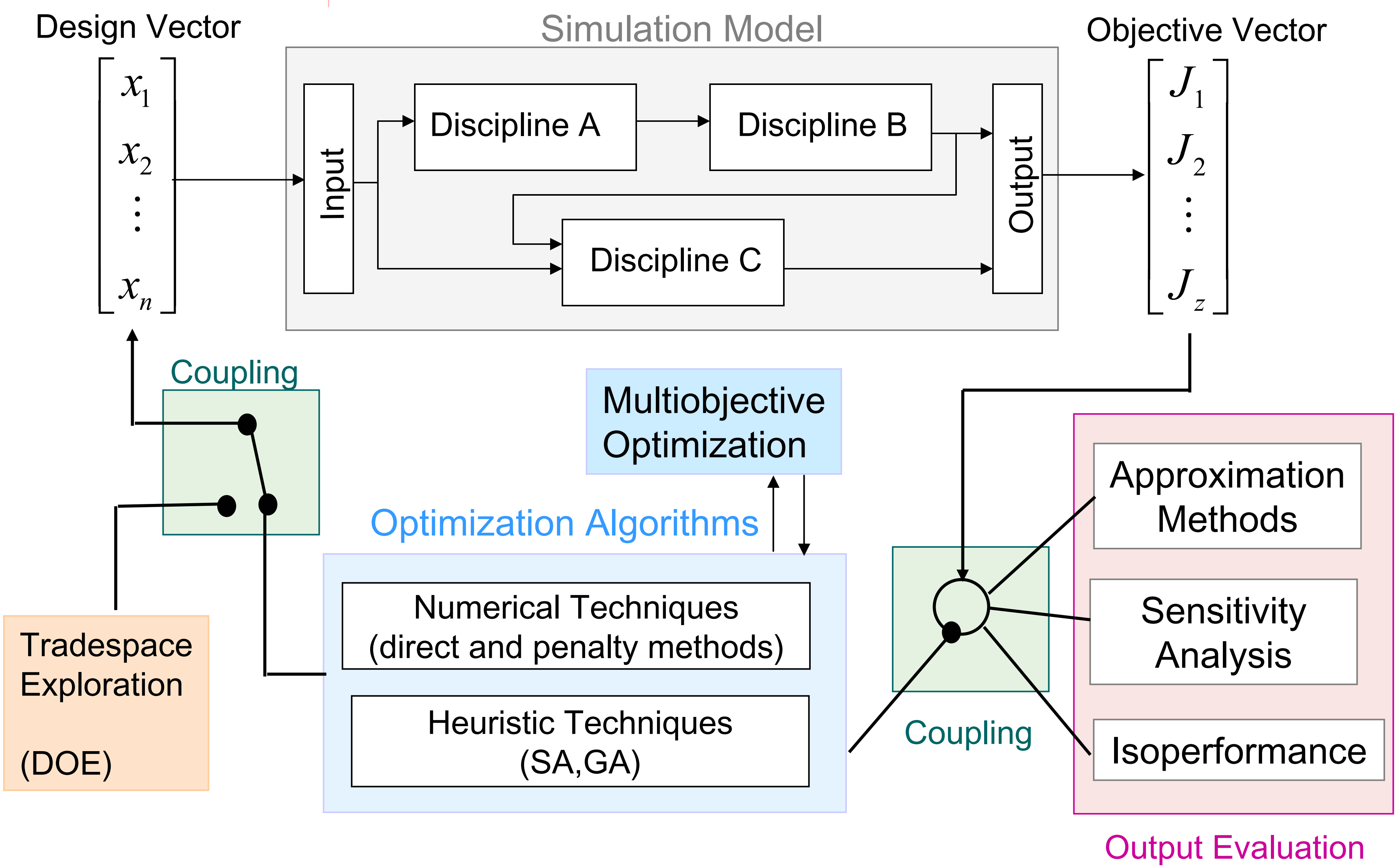
It does this by operating on a large number of variables and functions simultaneously - a feat beyond the power of the human mind.

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

MSDO Framework



Simulation versus Optimization

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 5).

Typical Process in MDO

(1) Define overall system requirements
(2) Define design vector **x**, objective **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(x)
(9) Post-optimality analysis to explore sensitivity and tradeoffs: sensitivity analysis, approximation methods, isoperformance, include uncertainty

In Practice...

(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

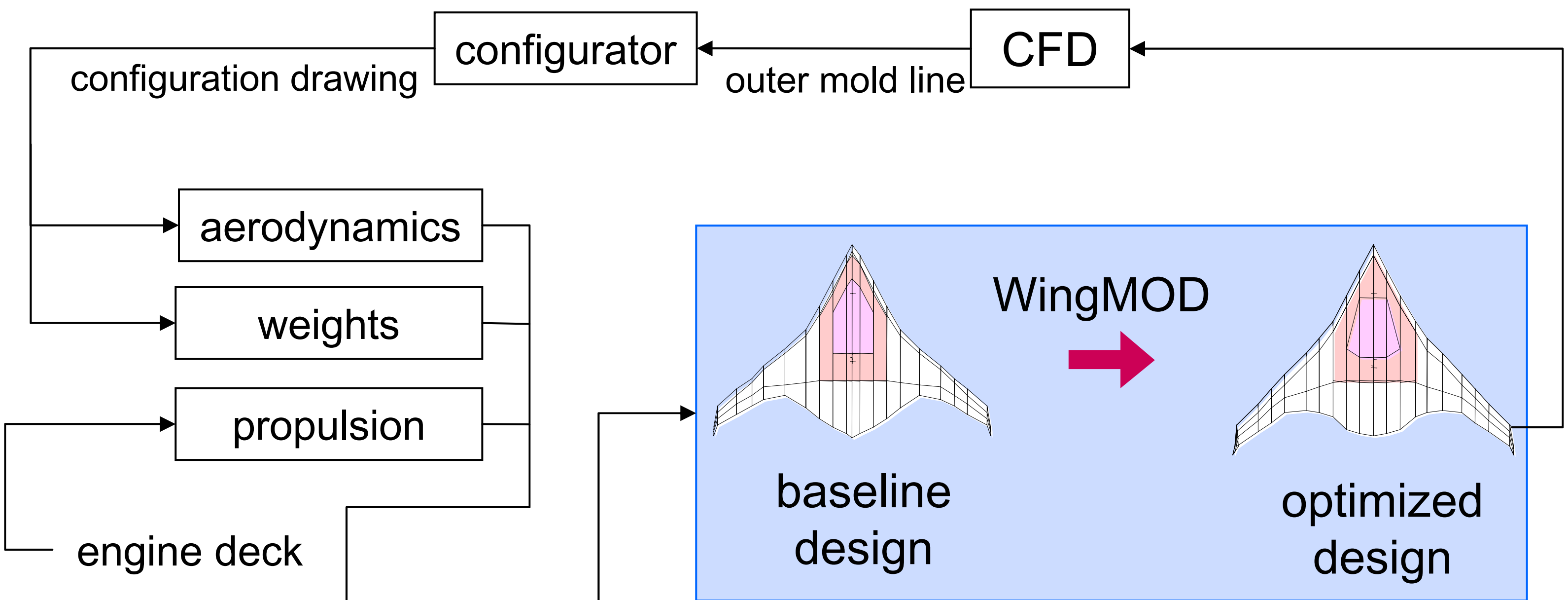
The optimizer will be unable to find a feasible solution (satisfies all constraints)

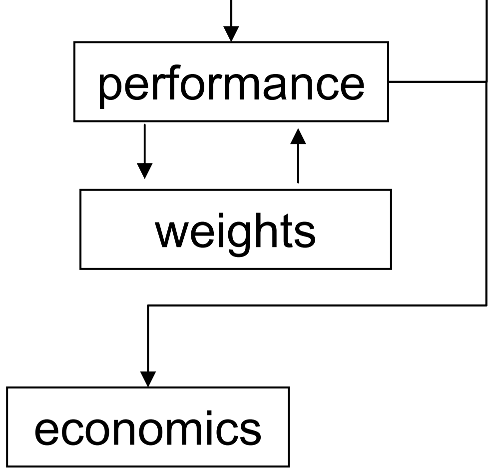
(iii) Add, remove or modify constraints and/or design variables

(iv) Iterate until an appropriate model is obtained

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

MDO in the Design Process

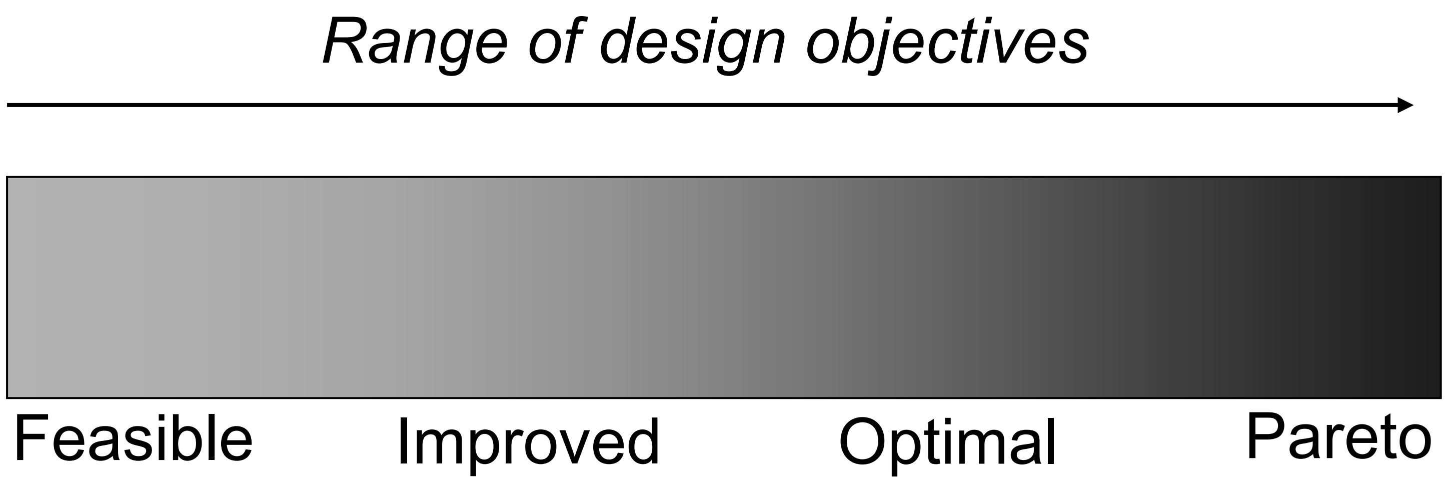




- MDO is only one part of the design process
- couples with other design tools
- invaluable but not always complete

MDO Uses

- 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 ...



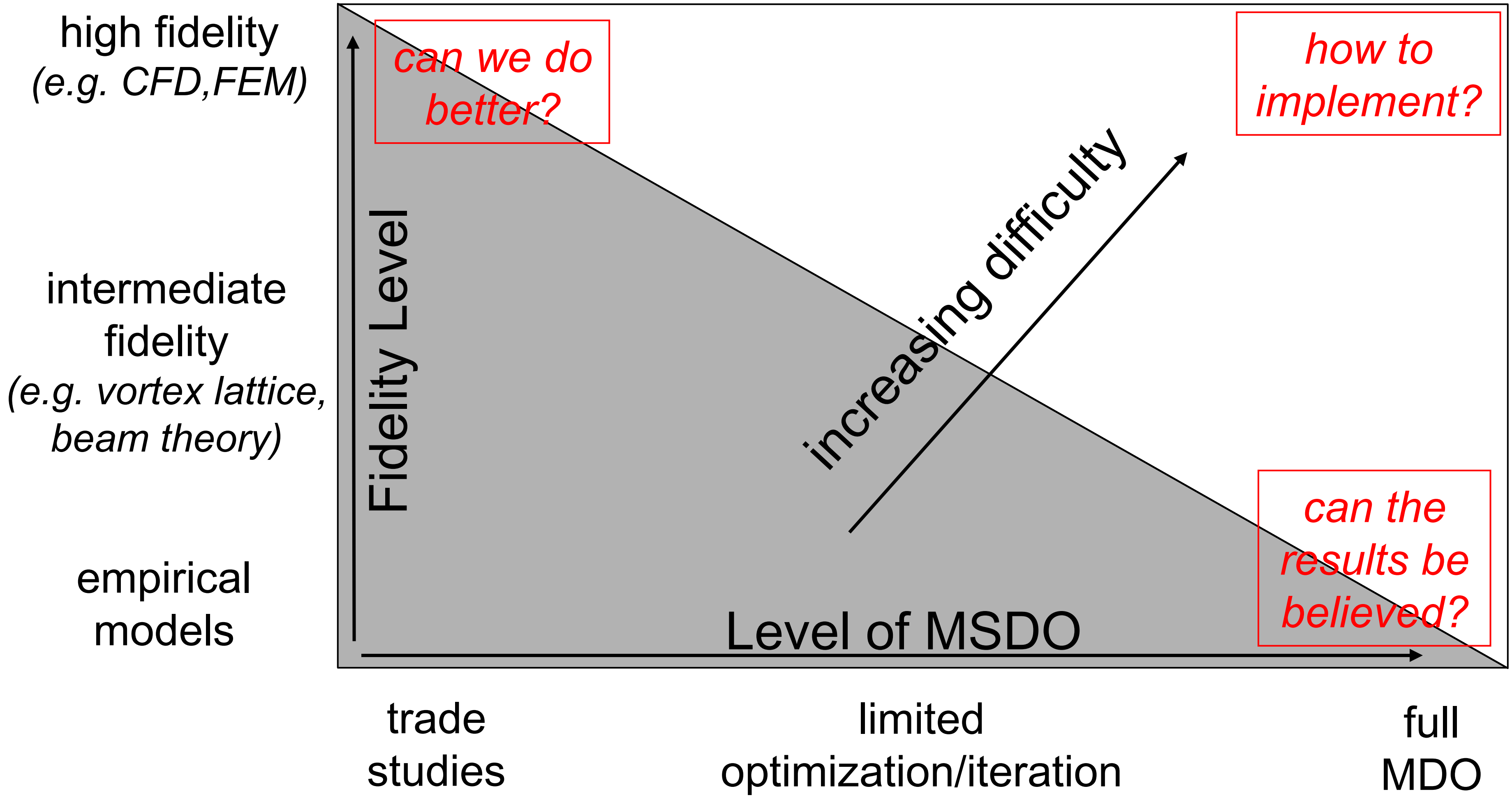
from Giesing, 1998

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?

Fidelity vs. Expense



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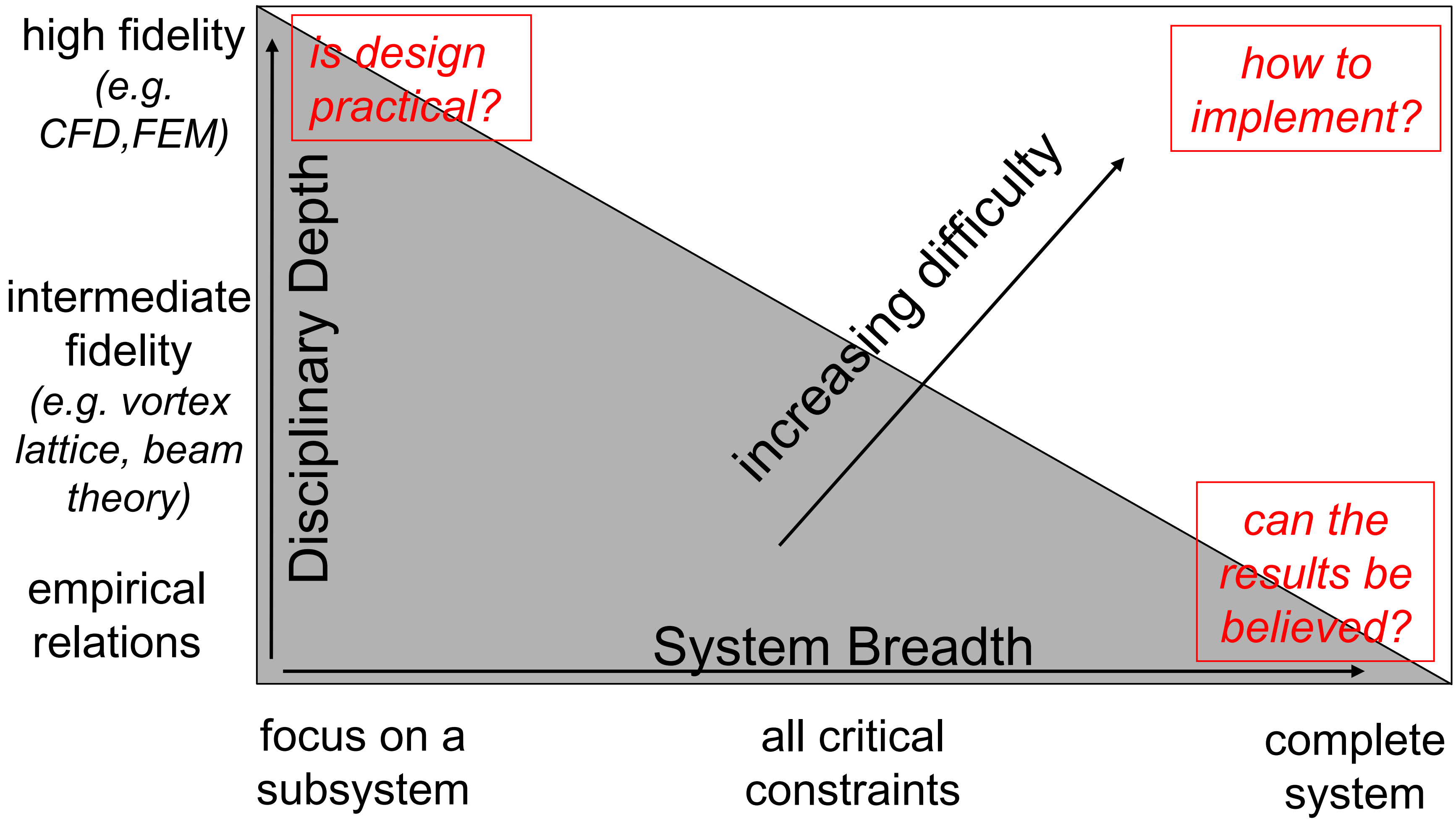
Breadth vs. Depth



MDO Pros/Cons

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

Data Management

- Need some kind of database to store design variables, constraints, objectives ...

  e.g. GenIE database
  ISight

- Would like to keep interface general and user friendly
  -don't "hard-code" problem specific details

- Can be a serious problem for large systems

Lecture summary

- 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

⇨ Guidelines of how decomposition and integration of modules can be done is the subject of Lecture 4

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