MULTICUBE EU-FP7- Project

POLITECNICO DI MILANO

Introduction to DSE and DoEs

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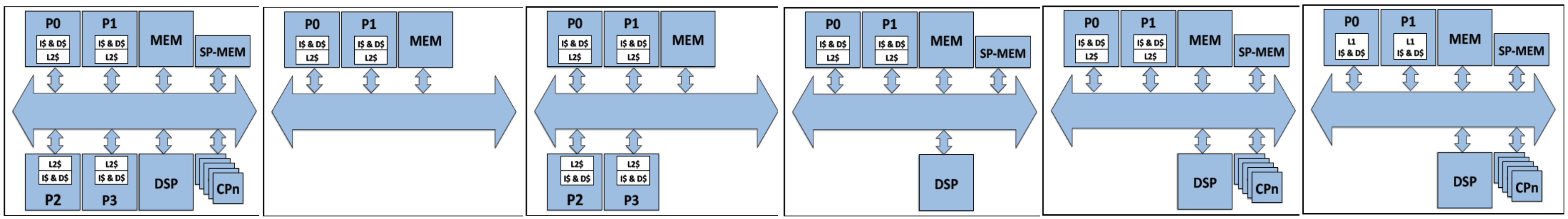
Some slides/images are also from – ESTECO – G.Palermo

Platform-based Design

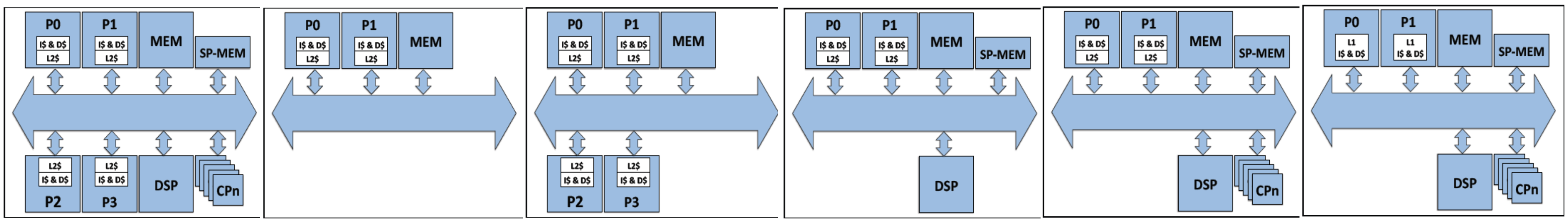
- *Hardware platforms* are used by vendors as reference designs for family of applications
  - ! Easy and fast customization to customers' requirements

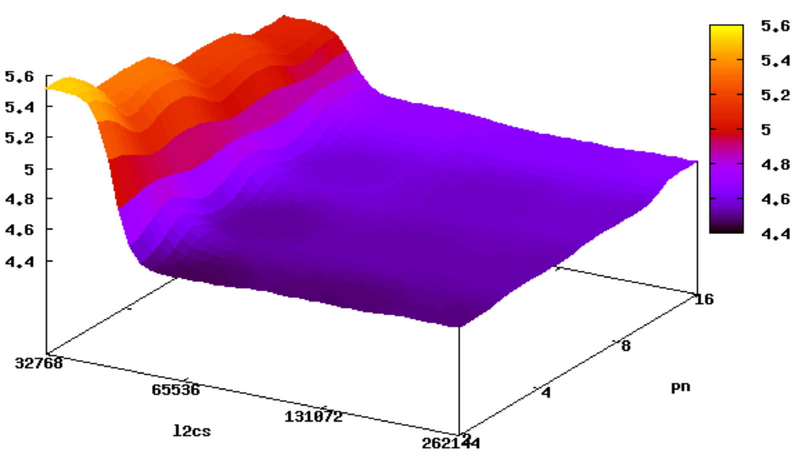


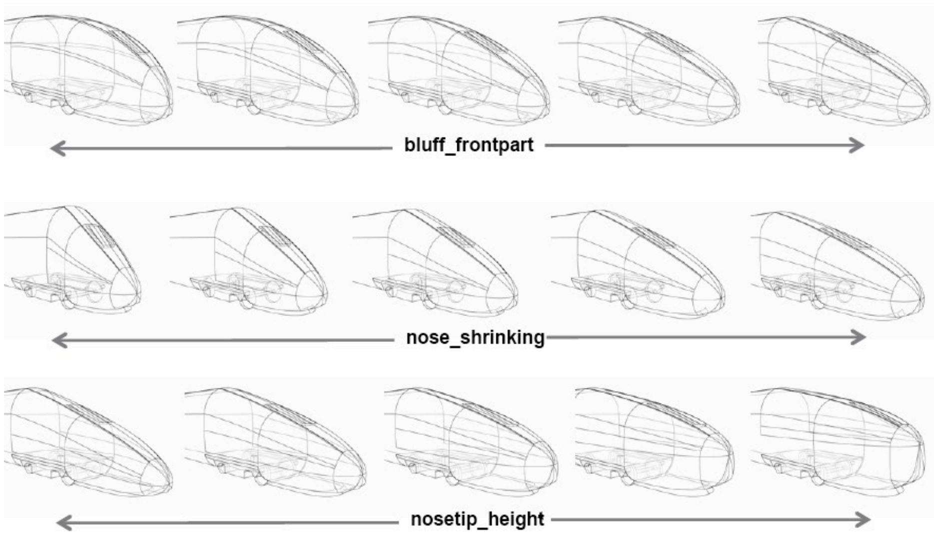
- The design based on *Hardware Platforms* enable:
  - Design-time customization targeted to a specific application
  - Pre-verified configurable IPs are instantiated and sized in order to meet application-specific constraints
  - Enables low-risk deployment while meeting time-to-market constraints
- The tuning process is called ***Design Space Exploration***

Customization and Design Space Exploration

- *Hardware platforms* are used as reference designs for family of applications
  - Easy and fast customization to application and customer's requirements
  - Pre-verified configurable IPs are instantiated and sized to meet application-specific constraints enabling low-risk deployment while meeting time-to-market constraints
- The tuning process is called *Design Space Exploration*

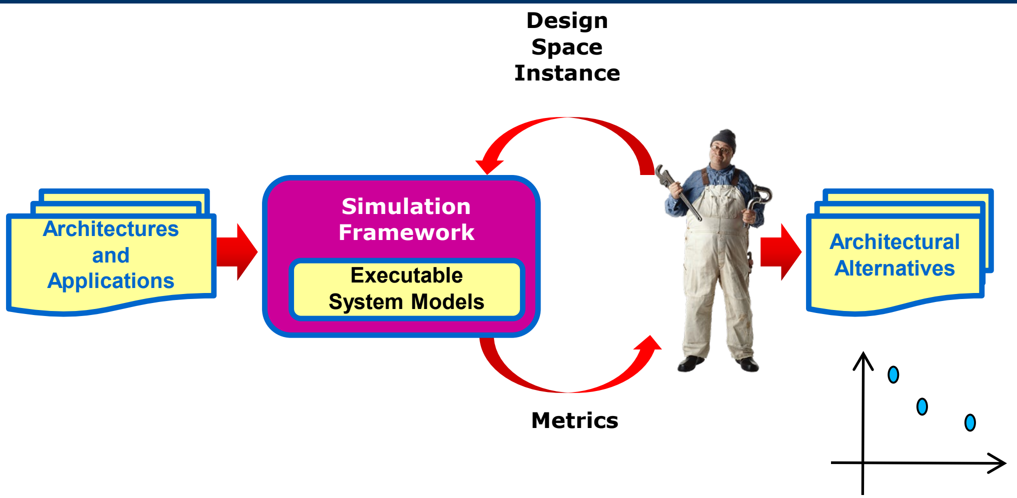


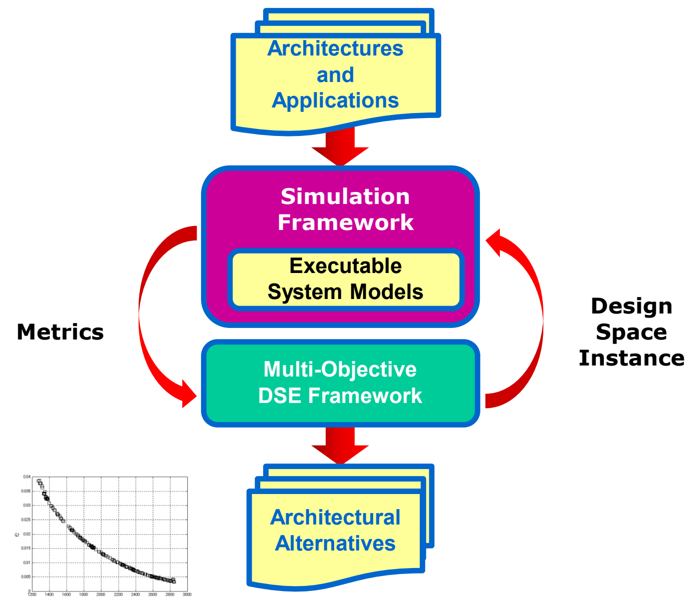




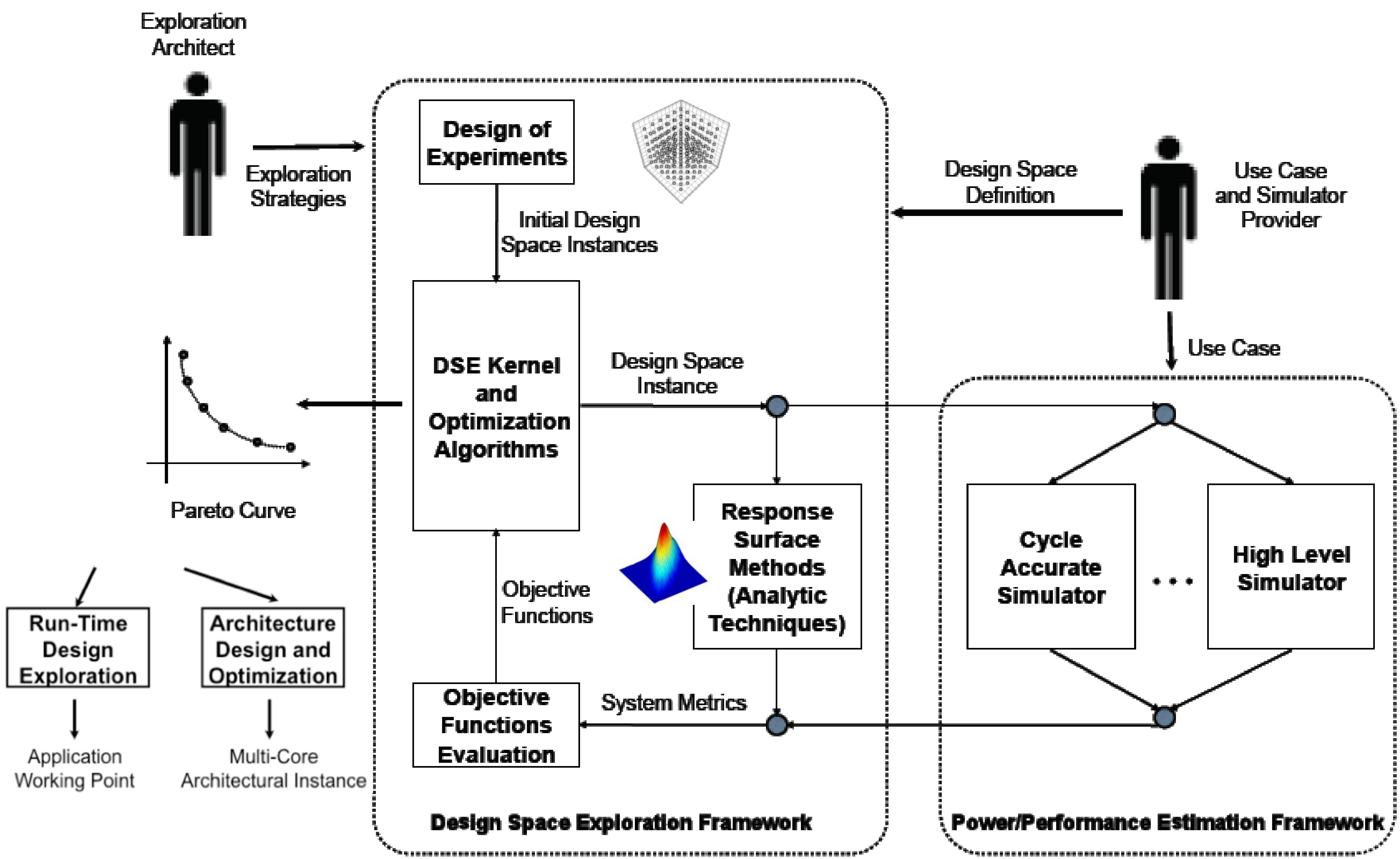
Design Space Exploration

- **Common view of the DSE problem**
  - Configurable Hw Platform
  - *Manual* Optimization by Designer Experience
- **Enhanced view of the DSE problem**
  - *High* Configurable Hw Platform
  - *Automatic* Optimization Framework
  - Commercial Framework:
    - **ESTECO modeFRONTIER**



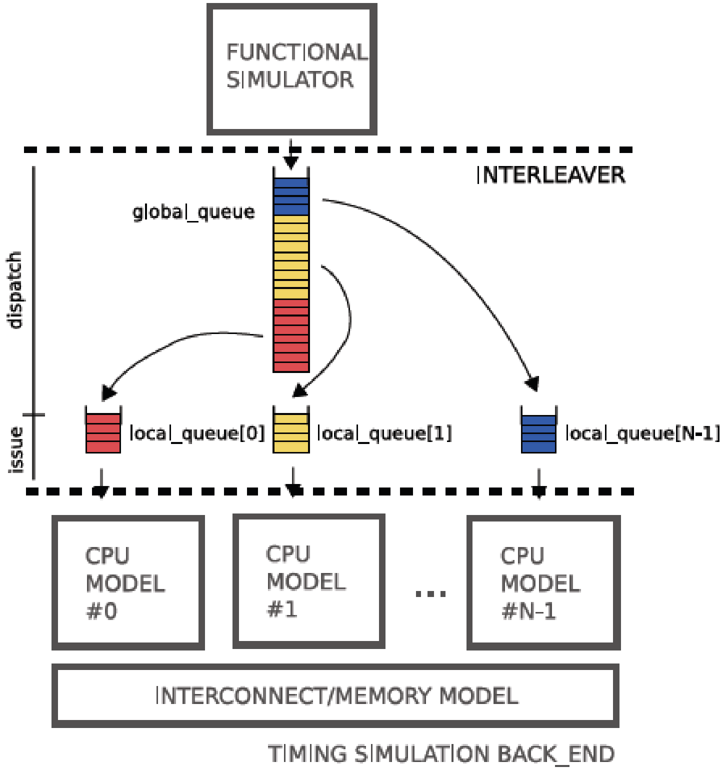


An ideal and complete design space exploration flow

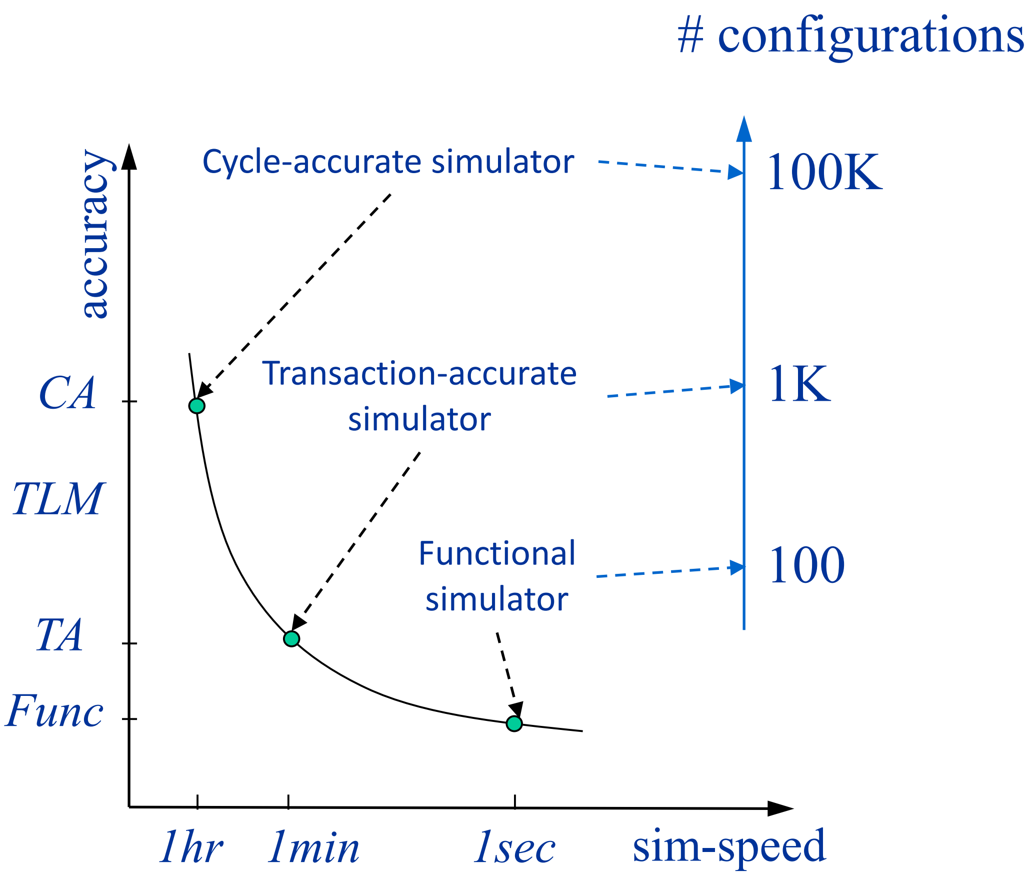


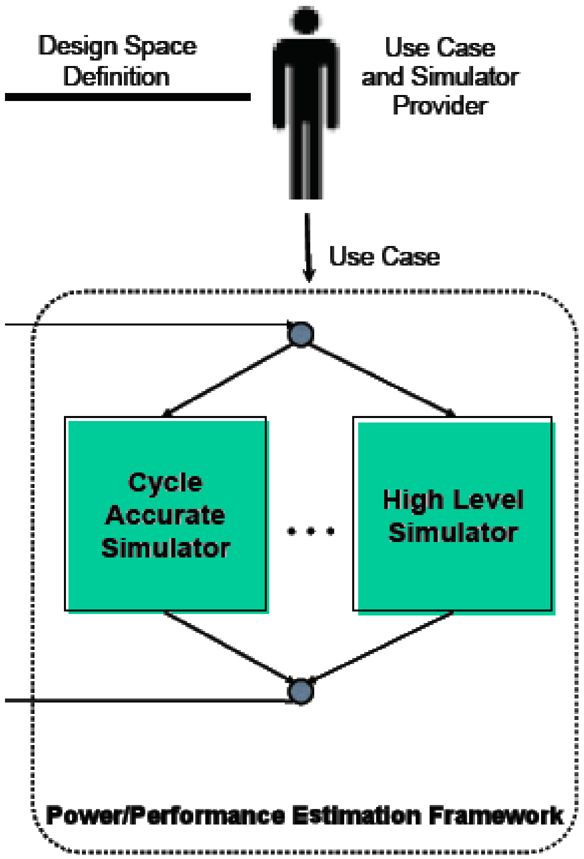
Simulation

- **How to simulate 1000 cores?**
- Simulating a large Chip Multiprocessor is an open problem for the computer architecture community
- Some existing simulators are able to simulate moderately-sized multi-core processors
  - low simulation speed (<10KCyc/sec)
  - scalability limit up to tens of cores



Multi-level Simulations





Some definitions

Definitions

- Optimization problem
- Input Variables
- Objectives
- Pareto Dominance
- Robustness and Accuracy
- Constraints

Need of optimization in design phases

... companies need to optimise their products and processes, ...

What is optimization?

Selection of the best option from a range of possible choices.

What makes it a complex task?

The potentially huge number of options to be tested

What qualifies as an optimization technique?

The search strategy

Multi-objective optimization

Optimization Problem

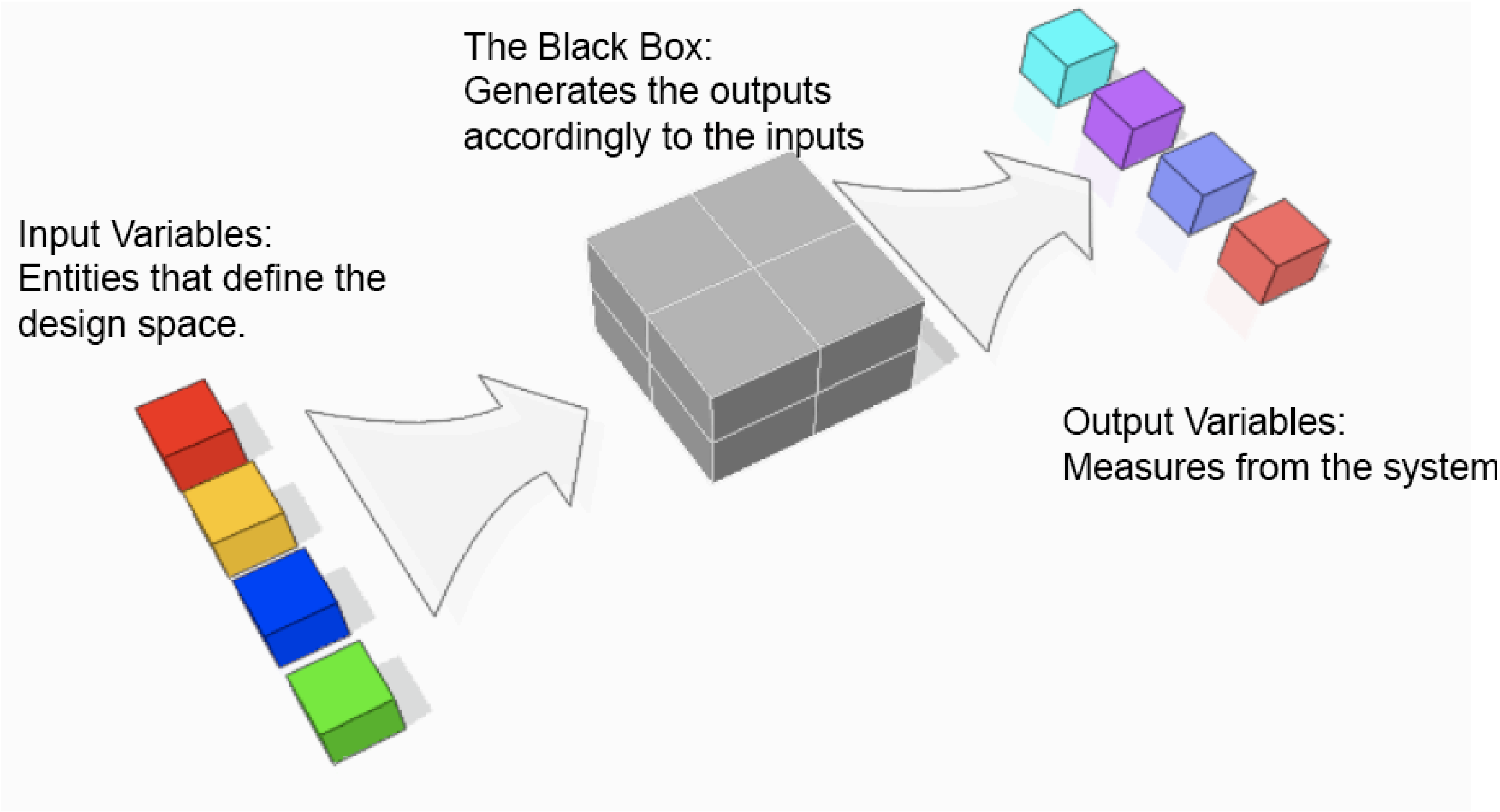
Mathematical formulation:

$$\max \; [f_1(x_1, \ldots, x_n), f_2(x_1, \ldots, x_n), \ldots, f_k(x_1, \ldots, x_n)]$$

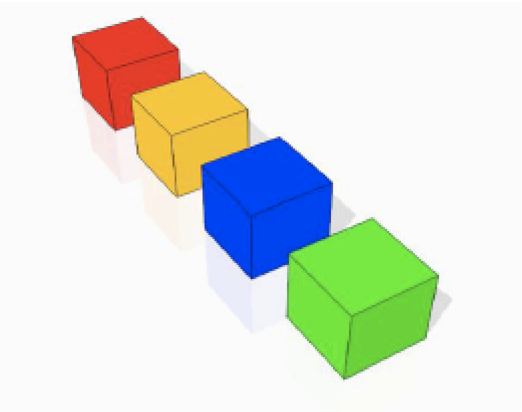
$$\text{subject to} \quad \begin{cases} g_i(\overline{x}) \leq 0 \\ g_j(\overline{x}) \geq 0 \\ g_1(\overline{x}) = 0 \\ \overline{x} \in S \end{cases}$$

When k>1 and the functions are in contrast, we speak about multi-objective optimization.

The concept behind the automatic DSE



Input Variables



Variables:

Variables are the free parameters, i.e. the quantities that the designer can vary or the choices the designer can make.

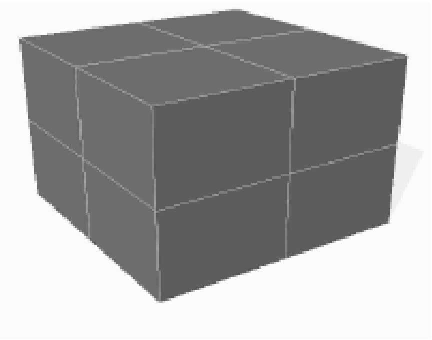
Continuous variables:

- point coordinates
- process variables

Discrete variables:

- components from a catalogue
- number of components

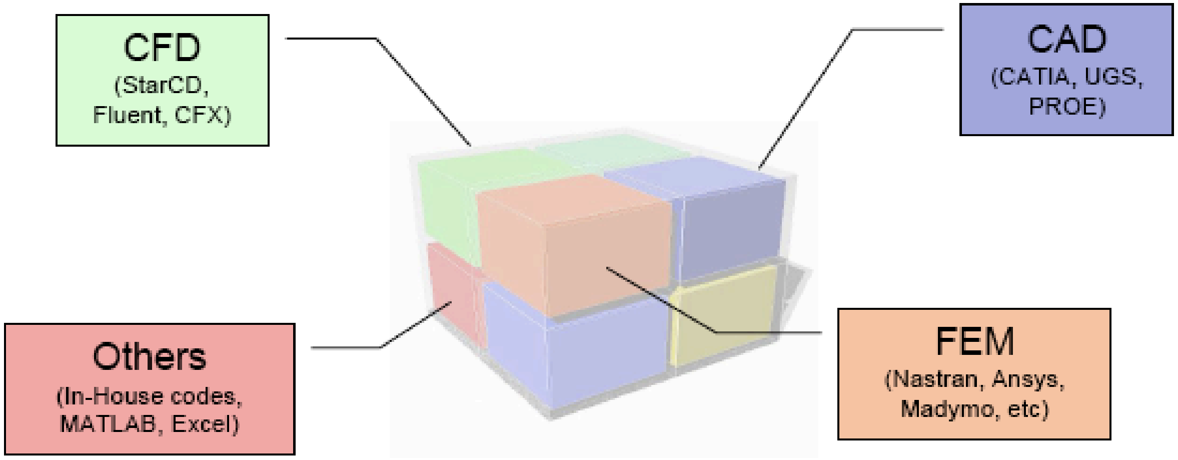
Black Box system model



The black box can be:

- A set of solvers that models and solves in a numerical manner the design problem (e.g. CAD/CAE tools)
- A set of experiments that produces some data

Multi-disciplinary Scenario



Optimization Objectives

Objectives:

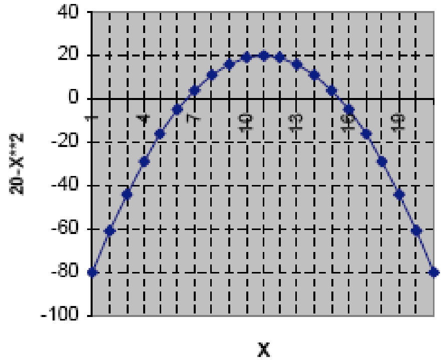
Objectives are the response parameters, i.e. the quantities that the designer wish to be MAX or MIN

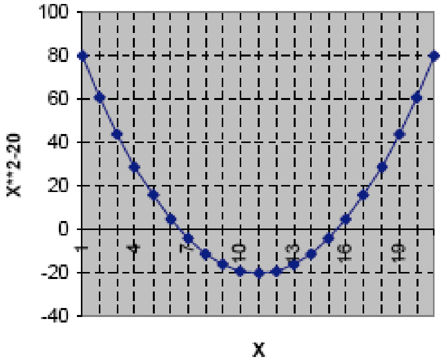
A MAX problem can always be transformed into a MIN problem.

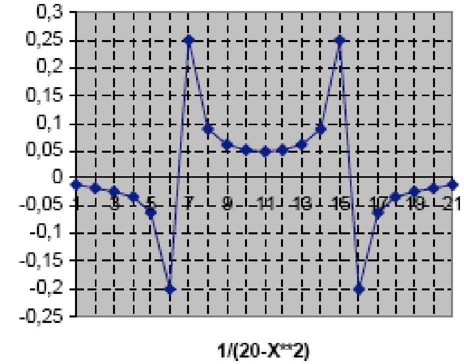
- MAX
  - efficiency
  - performance
  - etc…
- MIN
  - cost
  - weight
  - etc…

In order to transform a MAX into a MIN:

- $F_{new}(x)=-F(x)$ The problem is equivalent
- $F_{new}(x)=1/F(x)$ The problem is NOT equivalent ← Need attention!







Constraints

Constraints are the quantities imposed to the project, i.e. restrictions and limits that the designer must meet due to norms, functionalities, etc. They define a feasible region.

- **General constraints**
  - Max admissible stress
  - Max deformation
  - Max acceleration
  - min performance
- **Constraints on variables**
  - total volume
  - thickness
  - explicit function of the variables

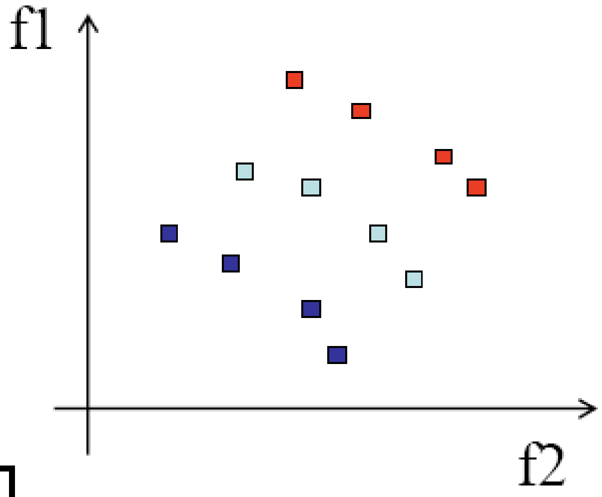
Pareto Dominance

- In the Pareto frontier none of the components can be improved without deterioration of at least one of the other component.
- Pareto dominance for one objective coincides with a classical optimization approach

a *dominates* b if and only if:

$$[f_1(a) \geq f_1(b) \textit{ and } f_2(a) \geq f_2(b) \ldots \textit{and } f_n(a) \geq f_n(b)]$$

$$\textit{and } [f_1(a) > f_1(b) \text{ or } f_2(a) > f_2(b) \ldots \text{or } f_n(a) > f_n(b)]$$

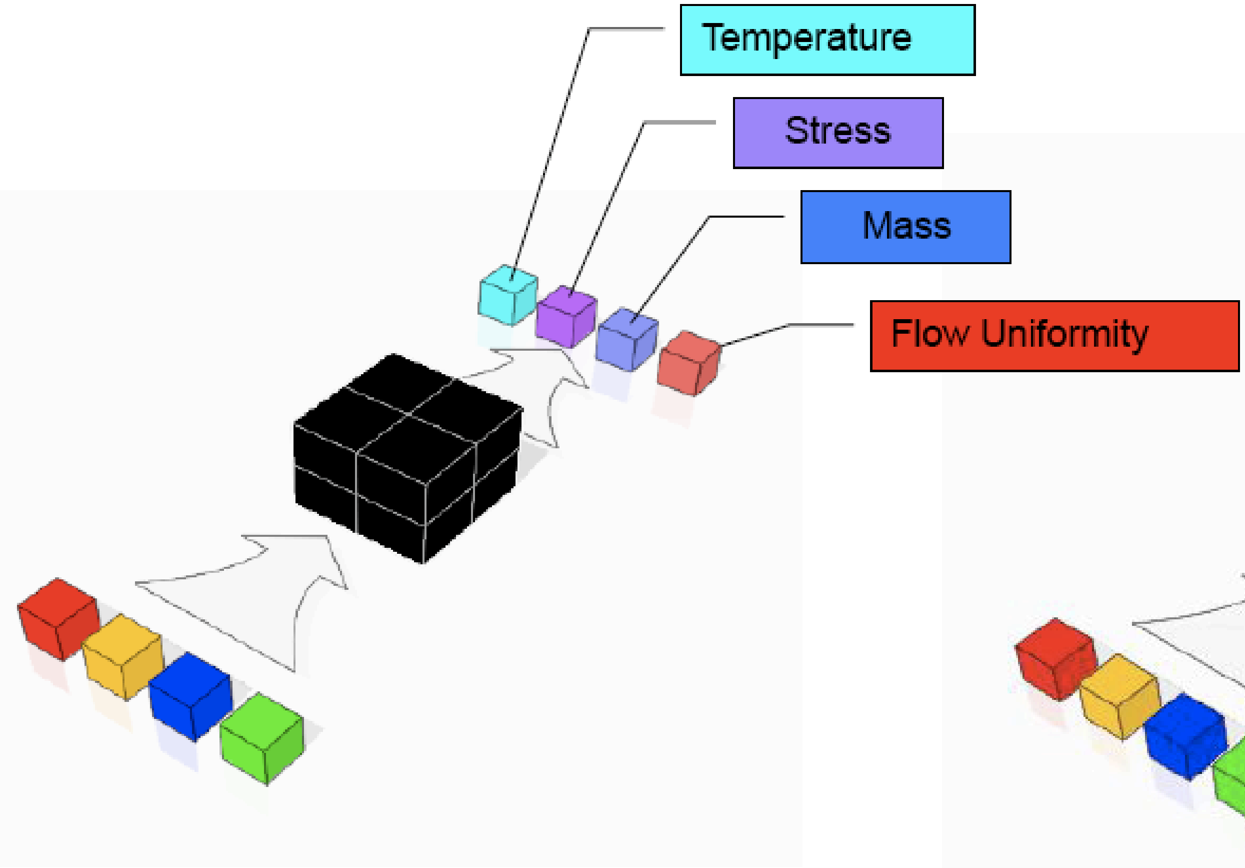


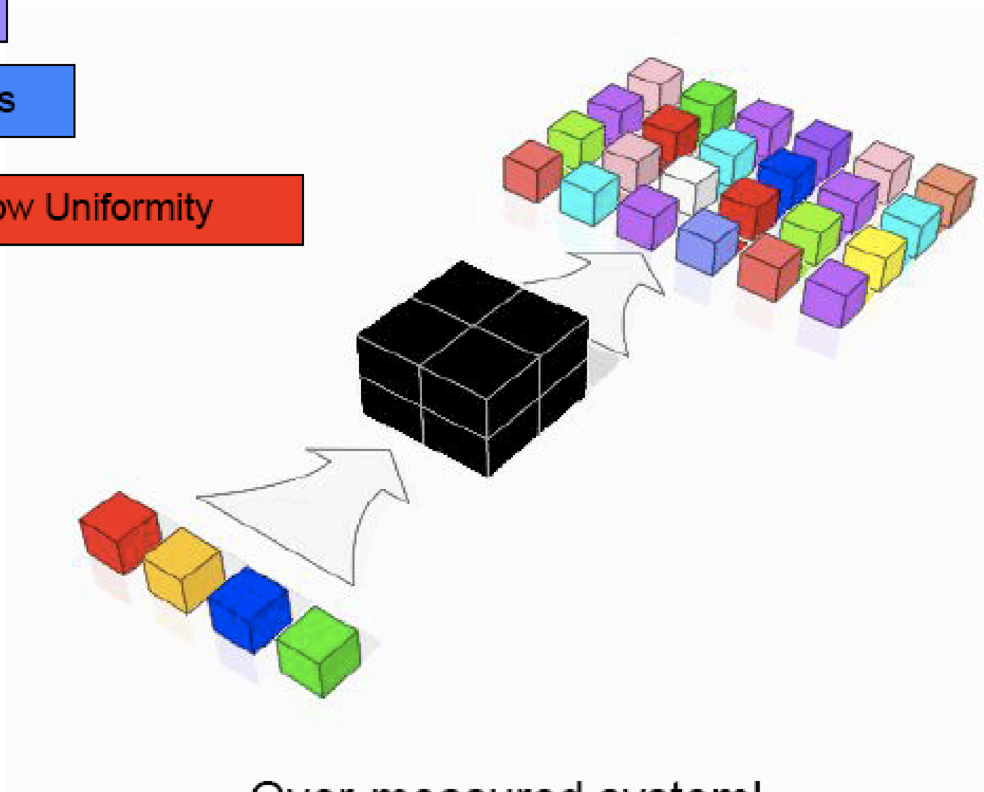
Red dots are the efficient solutions

The optimization algorithm must look for many, not one solution

The designers must take decisions

Output Variables: Over-measured systems





Over-measured system!

Another way to solve MOO-problems

Weighted Function:

- n objectives can be added in a single objective using weights:

$$F(x) = w_1{*}Obj_1 + w_2{*}Obj_2 + wj_3{*}Obj_3 \ldots$$

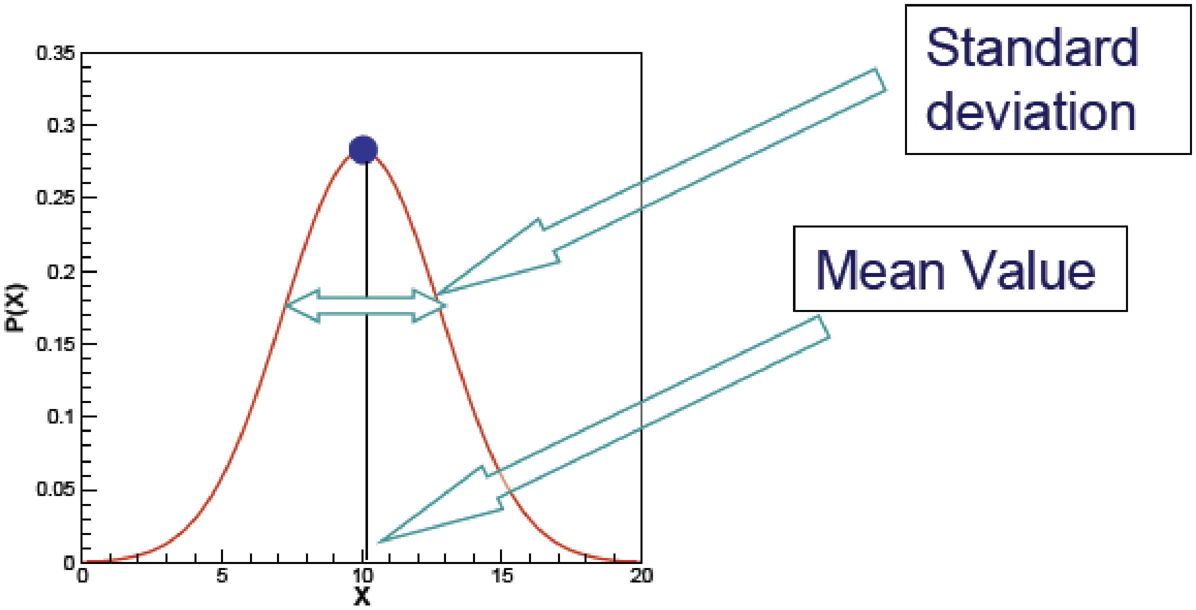
- Pro:
  - simple formulation
- Cons:
  - weights are problem-dependent and must be empirically defined
  - weights are connected to objectives values and might lose significance for different objectives values

Robust Design (1)

In many real world optimization problems, the design parameters are not fixed, normally we identify the **mean value** and the **standard deviation** of those parameters.

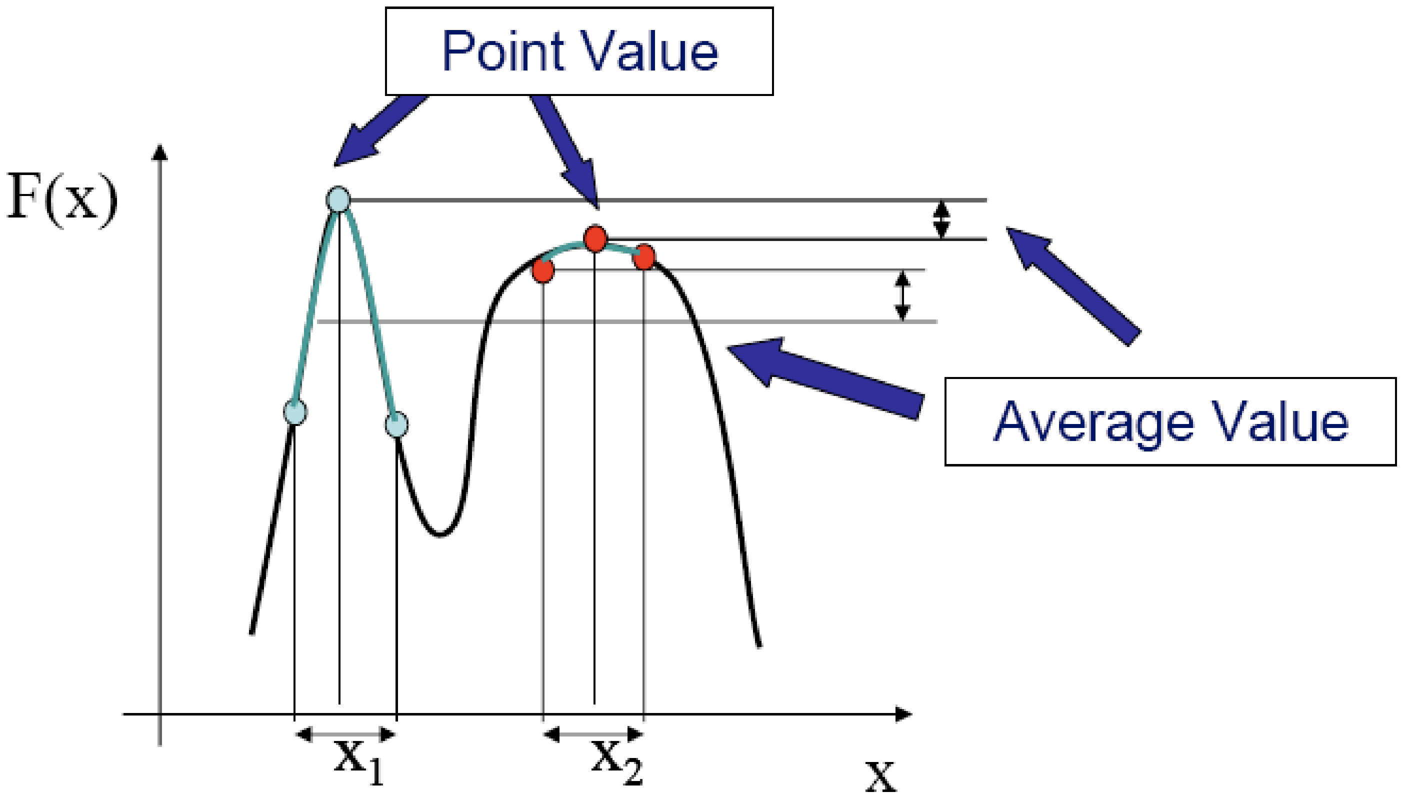
Example:

X=10 mm ± σ (=1.25 mm)



Robust Design (2)

Maximisation problem where the design parameters are defined by the mean and the deviation.

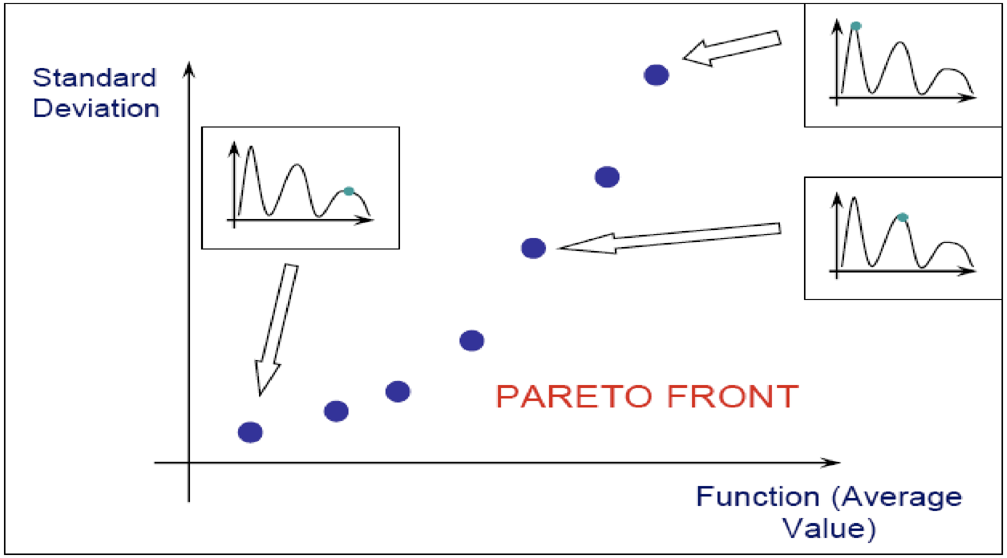


Robust Design (3)

- As we found out the **BEST ROBUST** solution could not be always identified with the **BEST GLOBAL** solution.

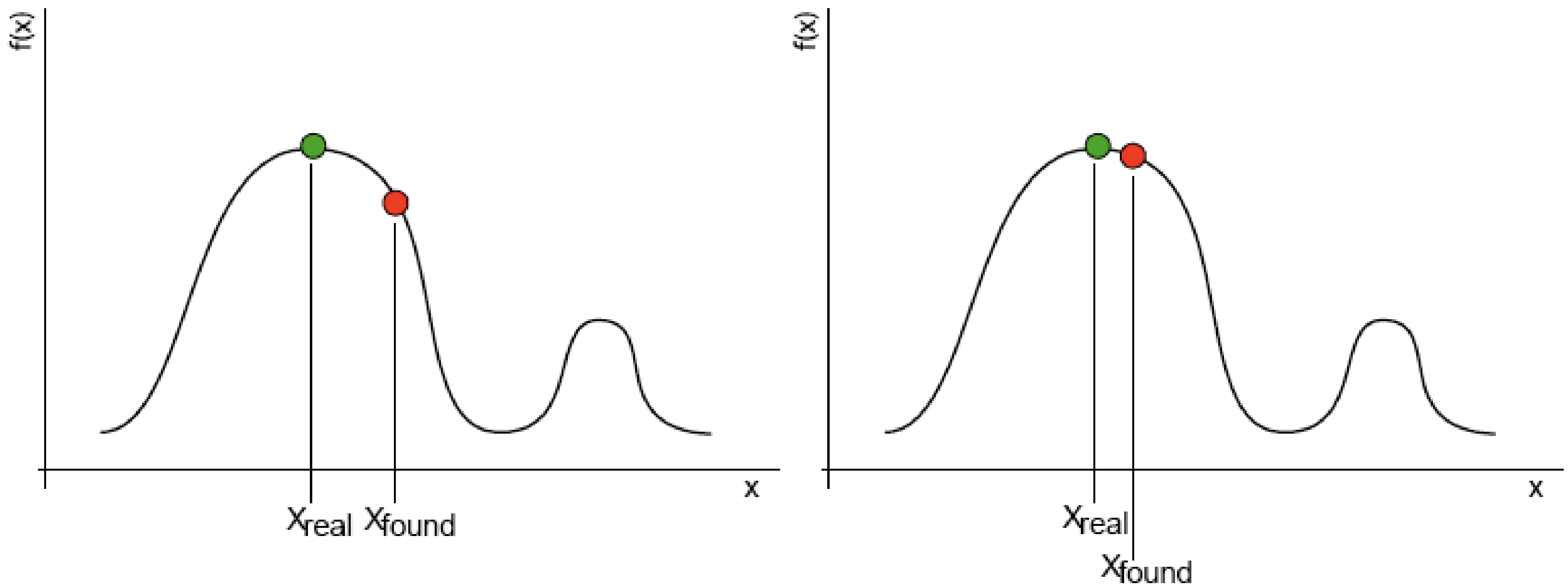
- For these reasons we have to introduce 2 different objectives:
  - **Maximize the average value** of the function inside the variables distribution;
  - **Minimize the standard deviation.**

- We need a **Multi Objective Algorithm** to address the Robust Optimization Problem.



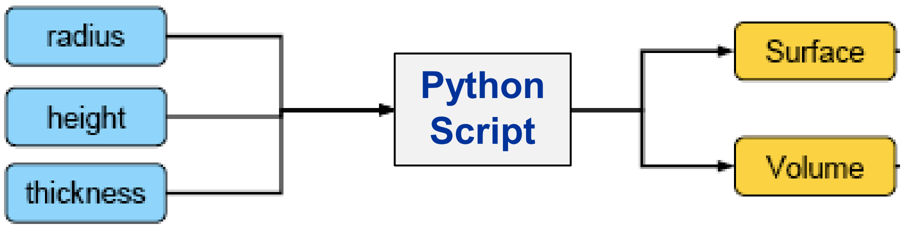
Accuracy in DSE

The accuracy measures the capability of the optimization algorithm to find the function's extreme.

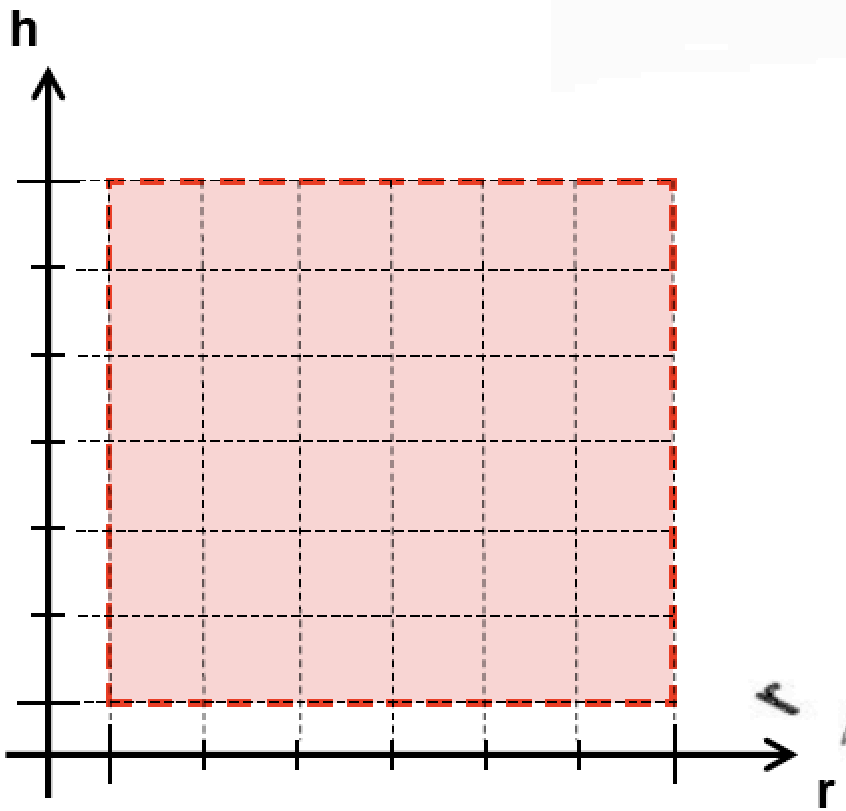


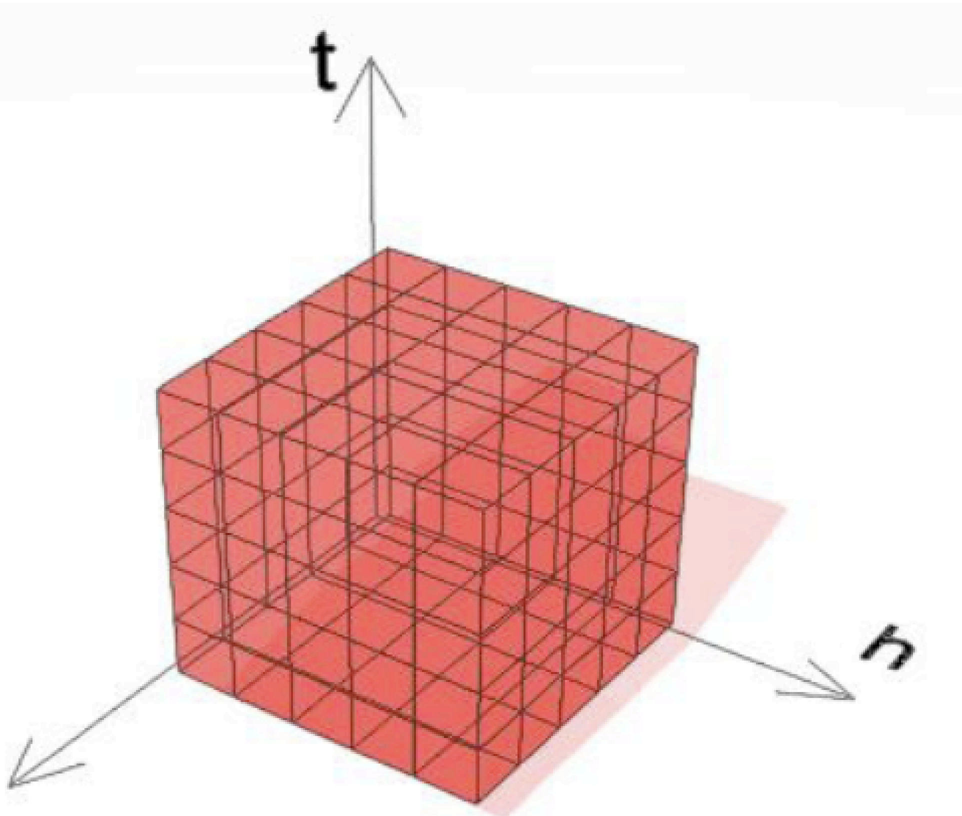
Beverage Can Example

- Inputs:
  - Radius “r”(from to cm)
  - Height “h”(from to cm)
  - Thickness “t” (from to cm)
- The Black Box model:
  - Python Script
- Outputs:
  - Surface = $2 \pi r^2 + 2 \pi r h$
  - Internal Volume= $\pi (r-t)^2 (h-2t)$

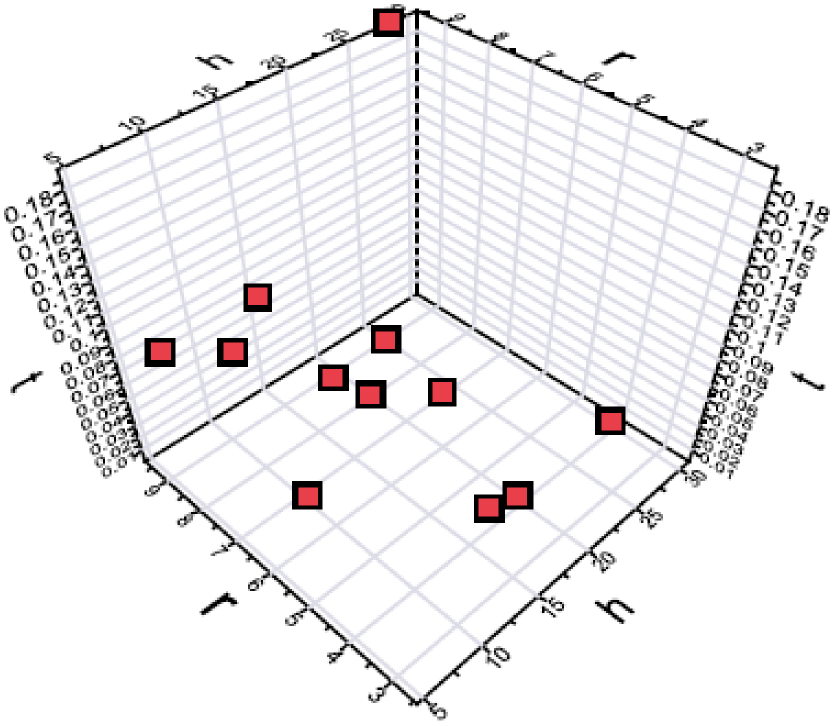


Design Space

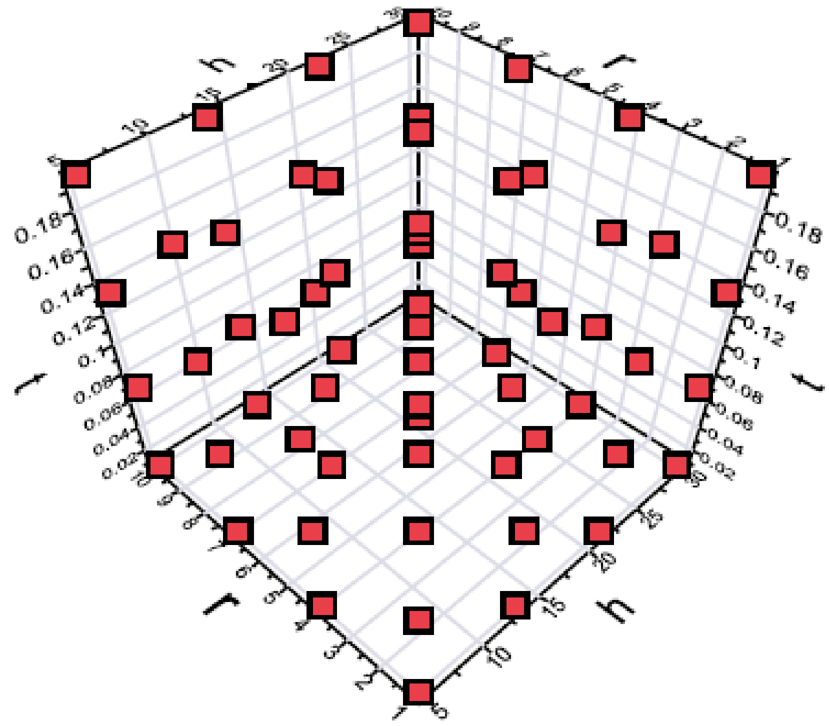




By designing the experiments to carry out
DESIGN OF EXPERIMENTS



Random DOE, 12 Entries

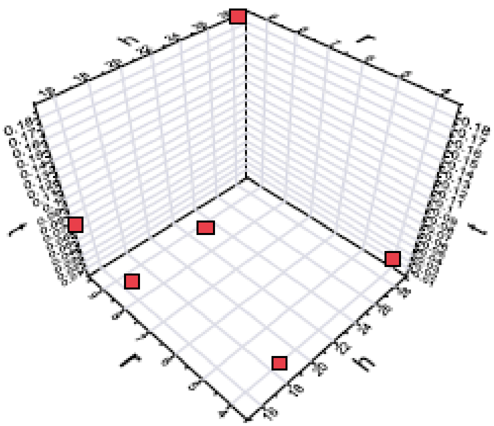


Full Factorial DOE, 64 Entries

The choice on the number of experiments: some examples

Aim of the Activity: have a good sample from laboratory tests for statistic study

Cost per Experiment: 1000 $

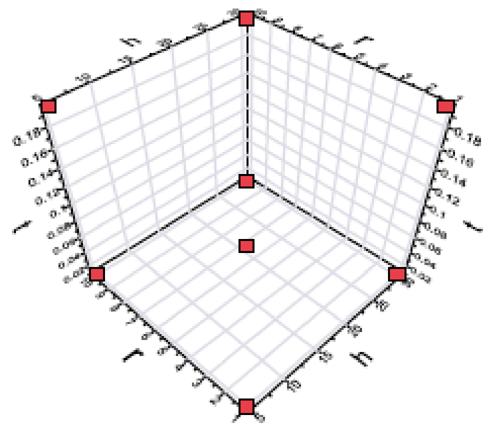


6 Random entries

Cost of the Campaign = 6,000 $

Cost

Quality

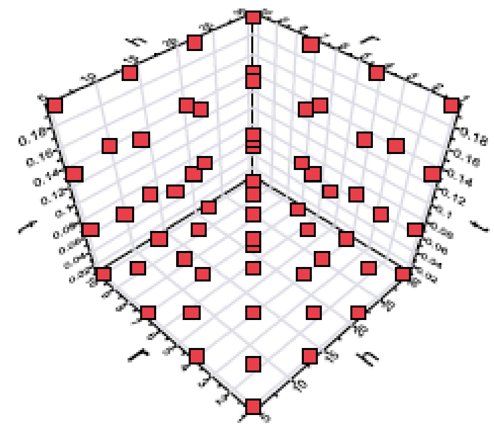


8 Full Factorial entries

Cost of the Campaign = 8,000 $

Cost

Quality



64 Full Factorial entries

Cost of the Campaign = 64,000 $

Cost

Quality

Why design of experiments?

- Shows **the statistical significance of an effect** that a particular factor exerts on the dependent variable of interest
- Extracts the maximum amount of **information regarding the factors affecting** a production process from as few (costly) observations as possible.
- Gathers information can be used to **build high-level models** of the process (linear regression).

- *The first statistician to consider a formal mathematical methodology for the design of experiments was Ronald A. Fisher.*

Full factorial designs, 2**k

- Factors have two levels which are encoded with '+' or '-', e.g.:

Factor	Levels '-'	Levels '+'
A. Instruction cache size	2KB	32KB
B. Data cache size	2KB	32KB
C. Instruction issue width	1	8
D. Inst. cache associativity	1	8

Full factorial designs, 2**k

- All the 2**k combinations are excercised on the target process.

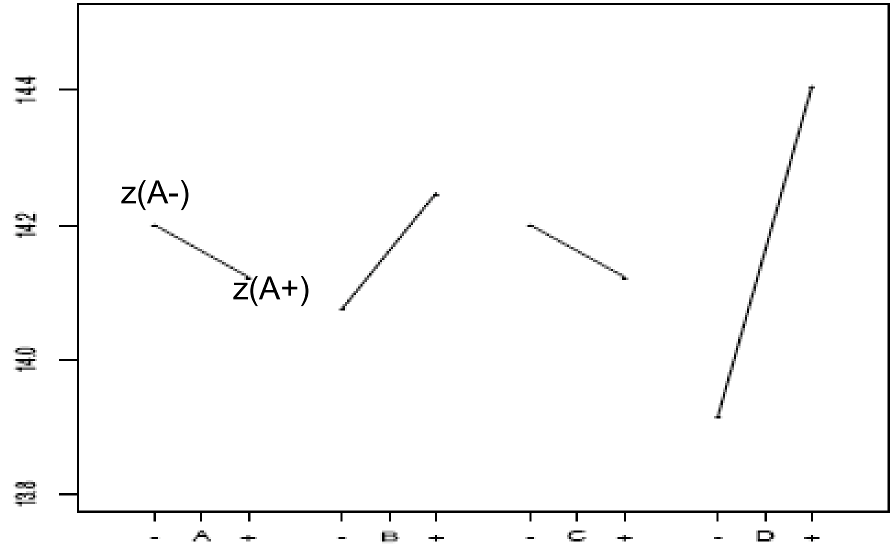
Run	Factor A	B	C	D	Delay (MC)
1	−	−	−	+	14.506
2	−	−	−	−	12.886
3	−	−	+	+	13.926
4	−	−	+	−	13.758
5	−	+	−	+	14.629
6	−	+	−	−	14.059
7	−	+	+	+	13.800
8	−	+	+	−	13.707
9	+	−	−	+	15.050
10	+	−	−	−	14.249
11	+	−	+	+	13.327
12	+	−	+	−	13.605
13	+	+	−	+	14.274
14	+	+	−	−	13.775
15	+	+	+	+	13.723
16	+	+	+	−	14.031

Full factorial designs, 2**k, main effects plot

- Given a target metric *y*, we define the main effect for factor A on *y* as:

$$ME(A) = z(A+) - z(A-)$$

- Where $z(A+) = \sum_i y_i \mid (A_i{=}+)/\text{count}(A_i{=}+)$
- z(A-) is defined analogously.
- Main effects plot for a set of factors:



Full factorial designs, factor interactions

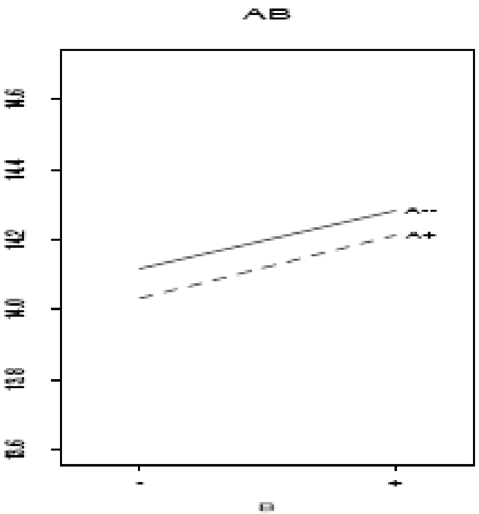
- Conditional main effect of B at + level of A:

$$ME(B|A+)=z(B+|A+)-z(B-|A+)$$

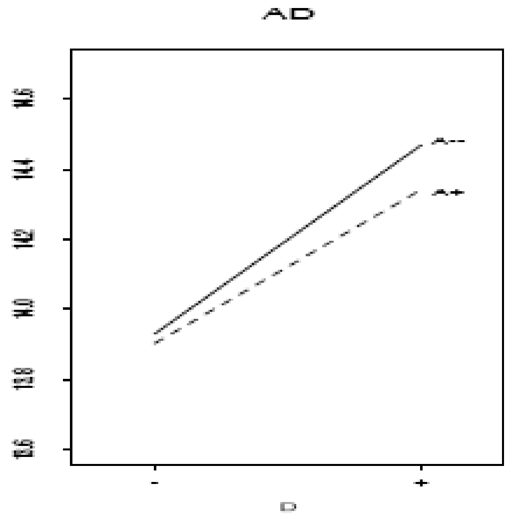
- Where $z(B+|A+) = \sum_i y_i \mid (A_i, B_i{=}+)/\text{count}(A_i, B_i{=}+)$
- Two factor interaction:

$$INT(A,B) = 1/2\{ ME(B|A+) - ME(B|A-)\} =$$
$$1/2\ \{ME(A|B+) - ME(A|B-)\}$$

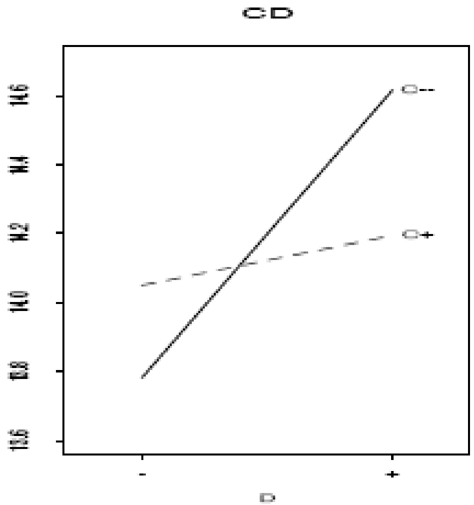
Factor interactions, continued



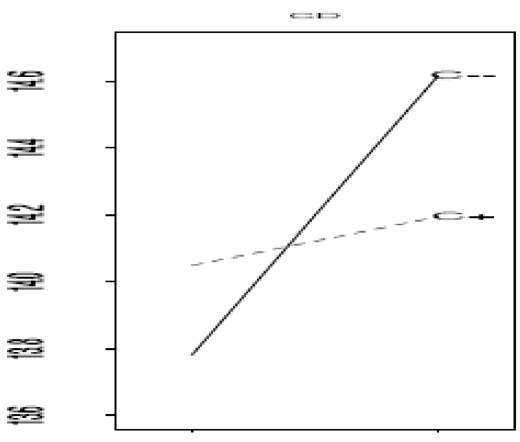
No interaction



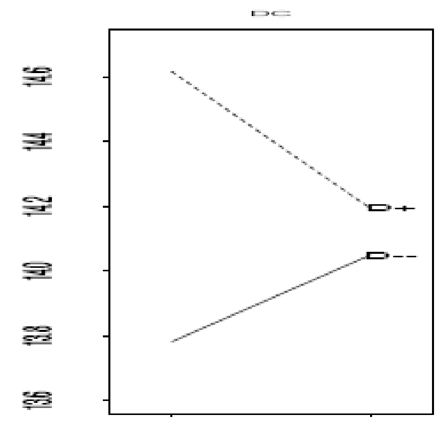
Mild interaction



Strong interaction

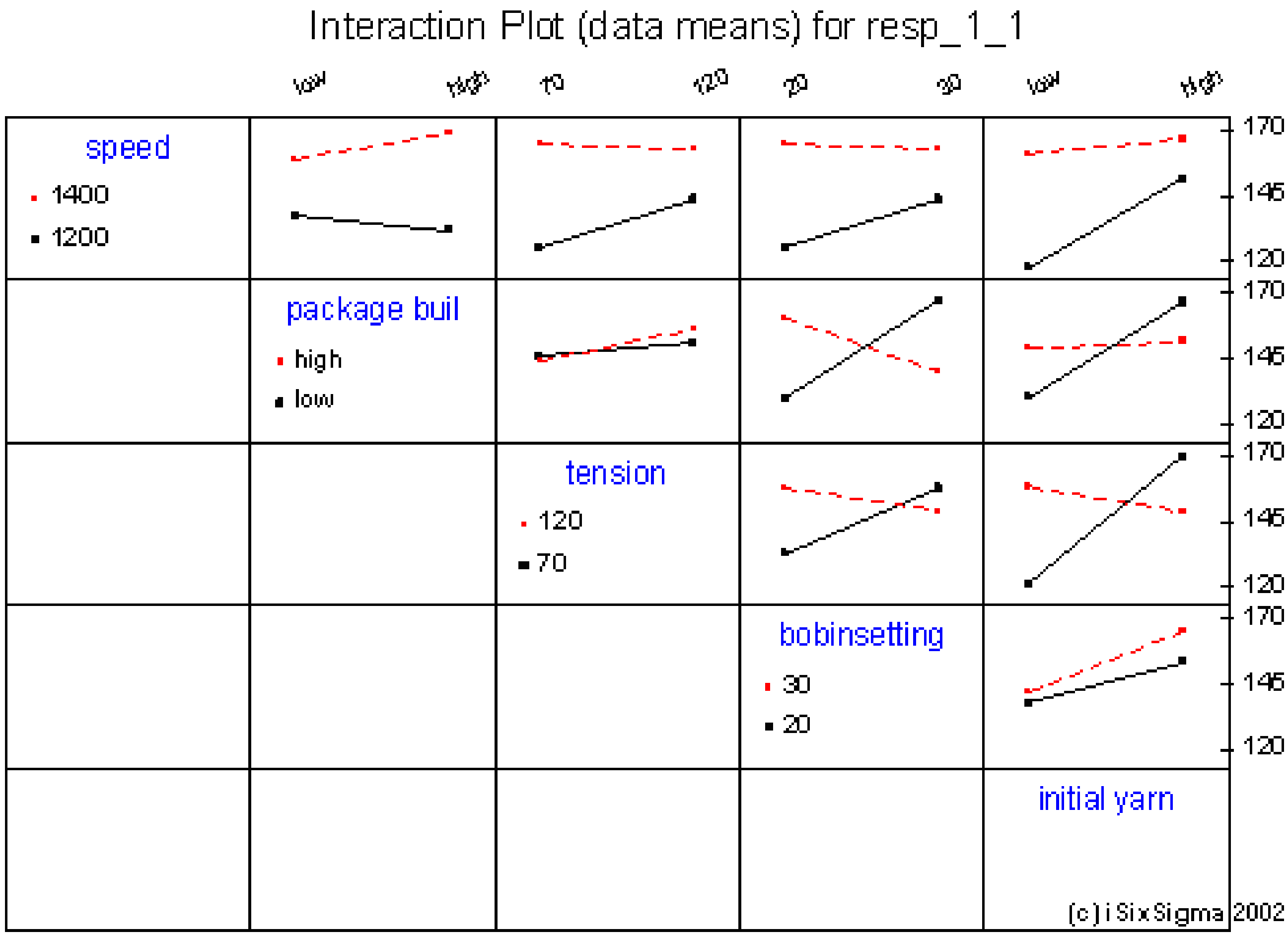


Synergistic strong interaction

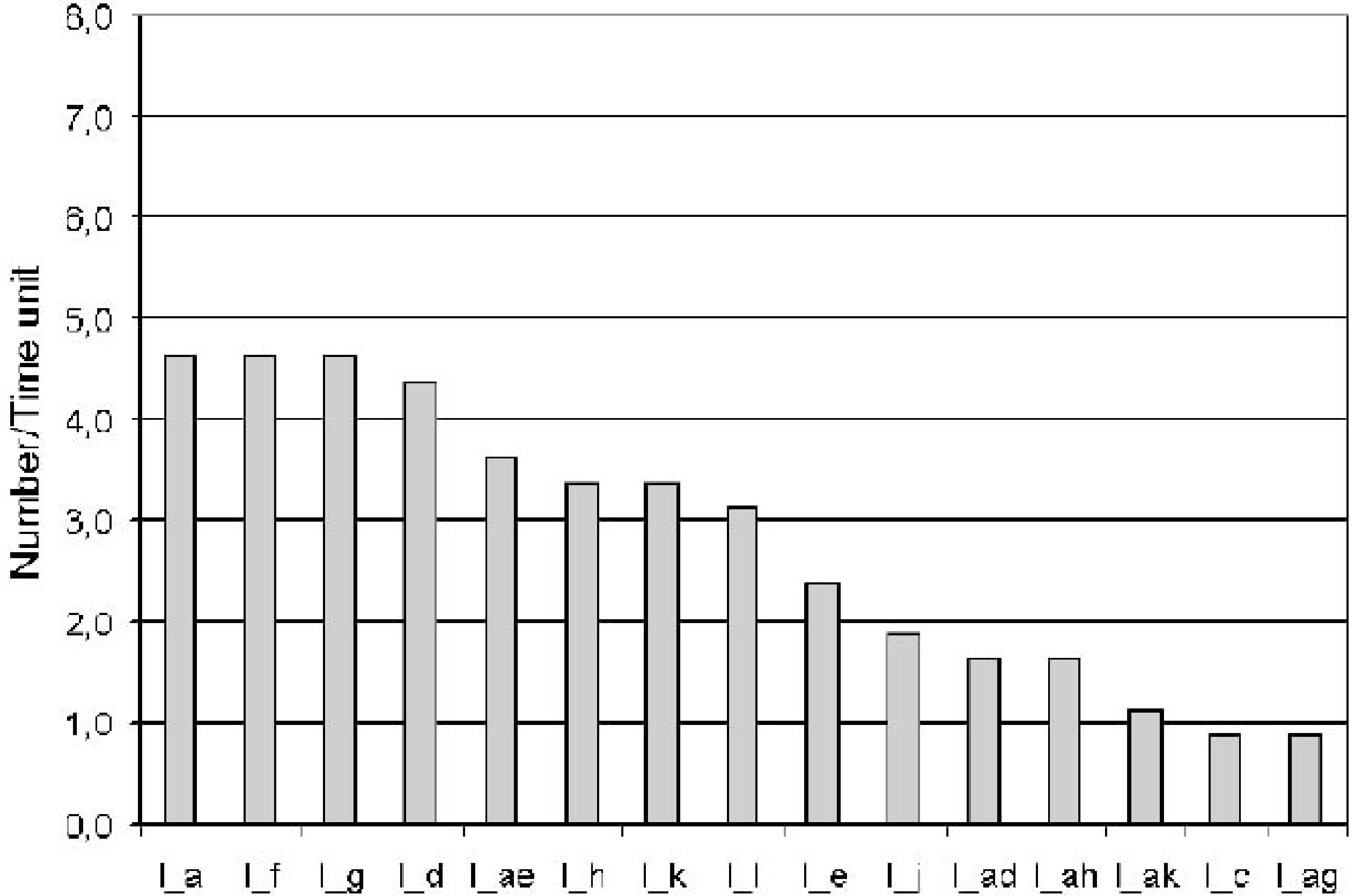


Antagonistic interaction

Factor interaction visualization



Factor interaction visualization, Pareto Diagram of interactions



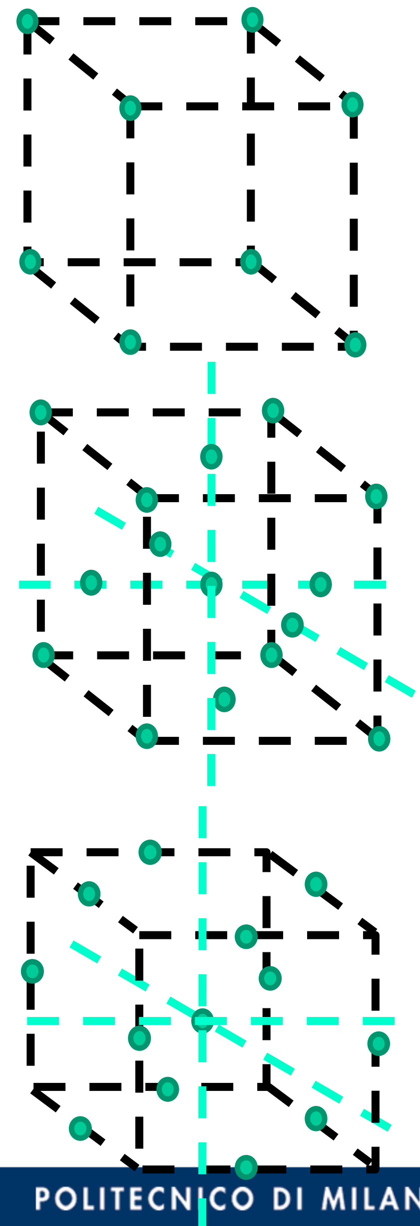
Fundamental principles in Factorial Design

- The following principles have shown to be true on the majority of industrial processes
- **EFFECT HIERARCHY:** Lower order effects are likely to be more important than higher order effects.
- **EFFECT SPARSITY:** The number of relatively important effects is likely to be small
- **EFFECT EREDITY:** In order to be significant, an interaction should have at least one of its factors to be significant

More DoEs (1)

- Identifies the planning of experimentation campaign where the set of tunable design parameters can vary
- Different in terms of the layout:
  - how to select the design points in the design space

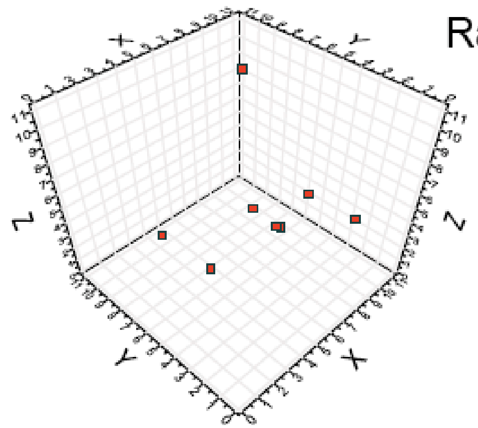
  - Full Factorial
  - Central Composite
  - Box Behnken



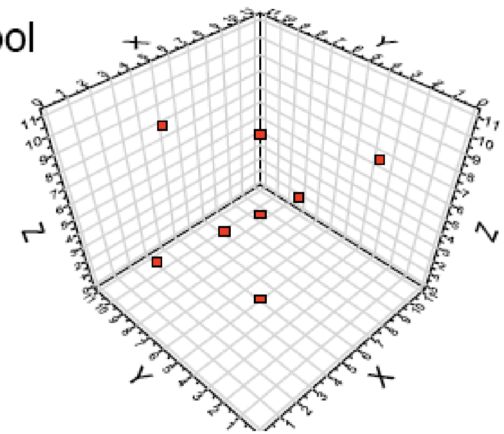
More DoEs (2)

Small Samples **(less than 10)**

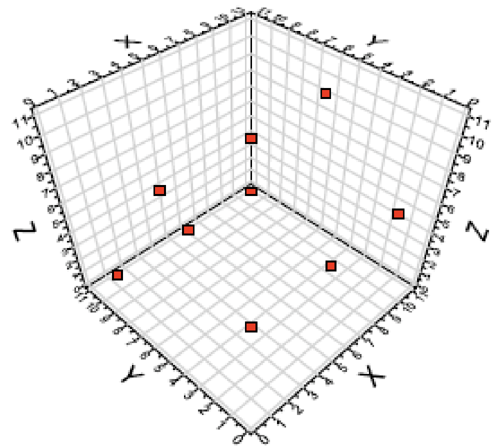
Random

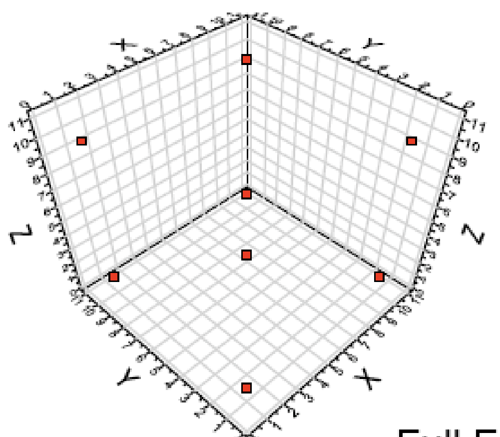


Sobol

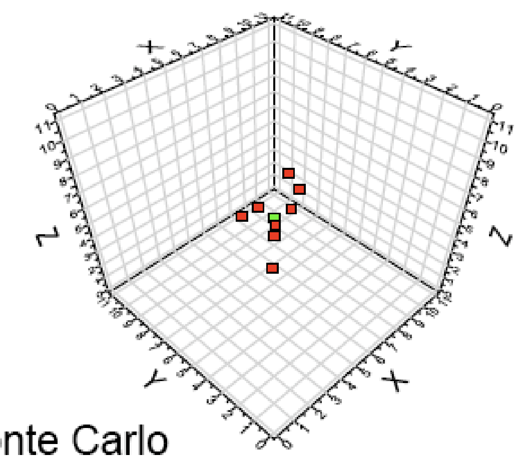


Latin Square





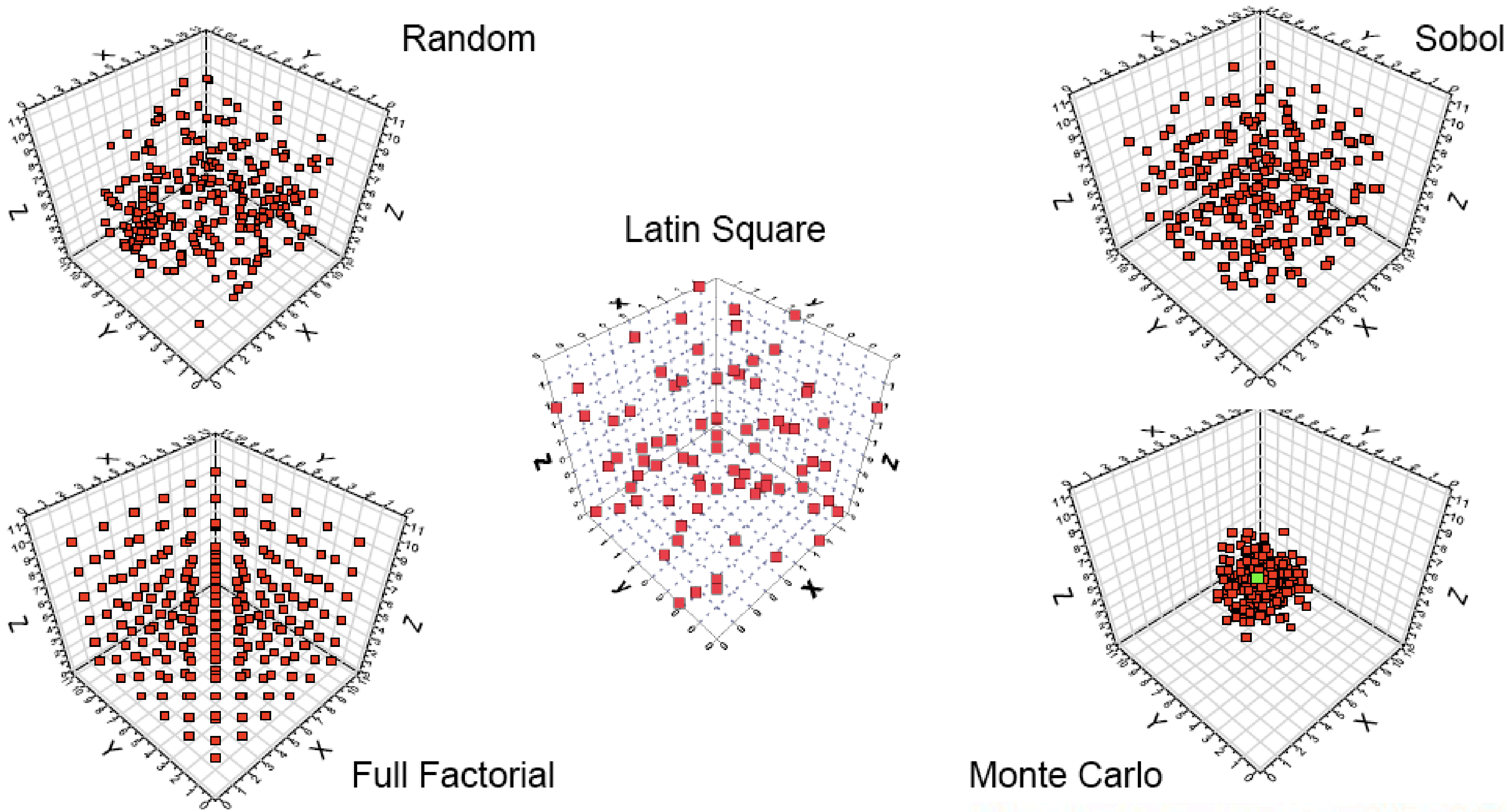
Full Factorial



Monte Carlo

More DoEs (3)

Big Samples (more than 200)



Explore new Frontiers of Innovation

Response surface methodology

- Response Surface Methodology is a technique used to **create mathematical models** for the relationship between one or more responses and a set of input variables.
- The model functions which we investigate are polynomials of the first order:

$$a_0 + \sum_{i=1}^{n} a_i x_i$$

- First order + interaction coefficients:

$$a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=i}^{n} a_{ij} x_i x_j$$

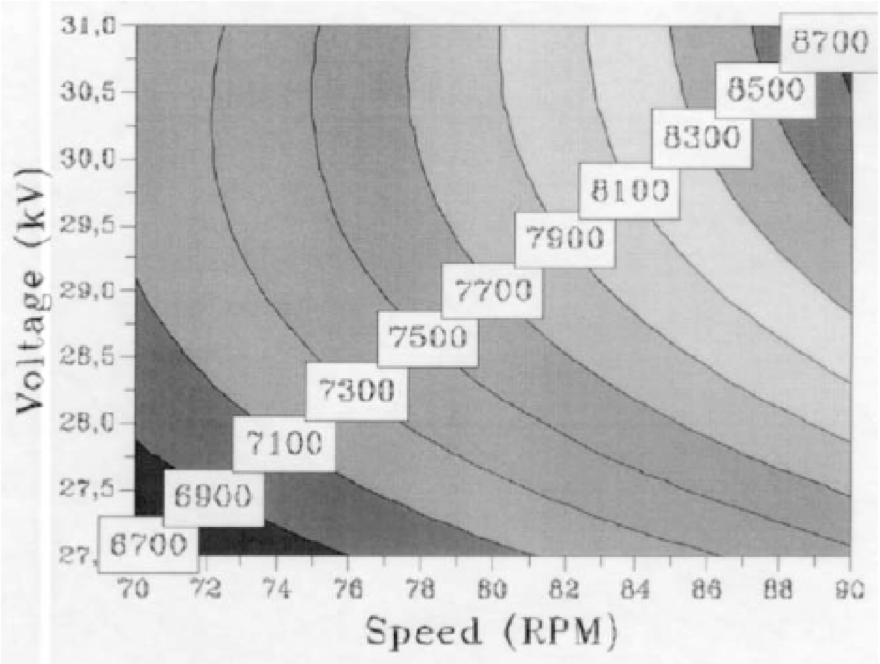
- Second order:

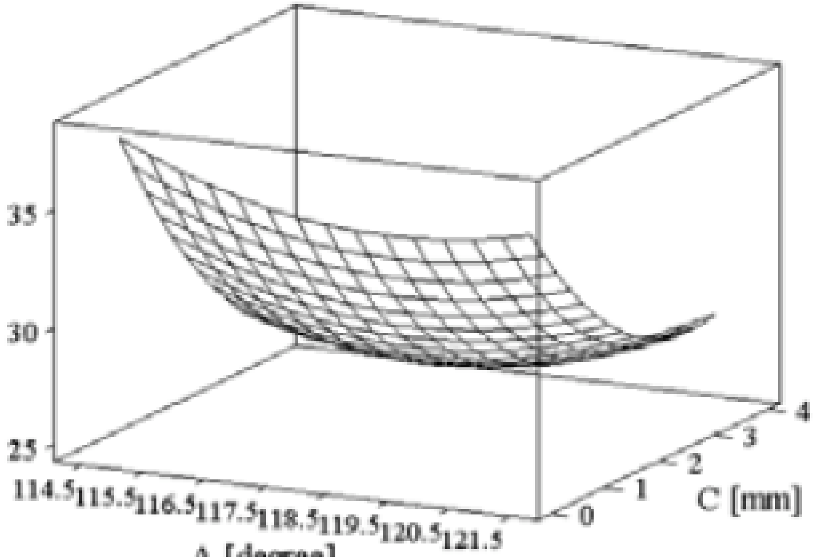
$$a_0 + \sum a_i x_i + \sum a_{i,j} x_i x_j + \sum a_{i,i} x_i^2.$$

- Higher order polynomials can be introduced, depending on the complexity of the observed effects.

Response surface methodology

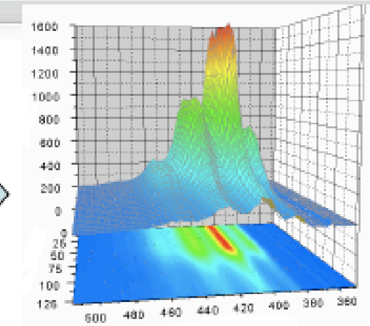
- Linear and linear+interaction models can be fitted from data coming from a two-level analysis (Full Factorial/Fractional Factorial)
- Quadratic and higher order models should be fitted with data coming from second order DoE like CCD and three level factorial designs.
- Once fitted, models can be used to perform various analysis and optimizations.



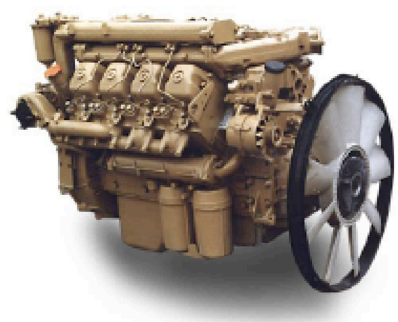


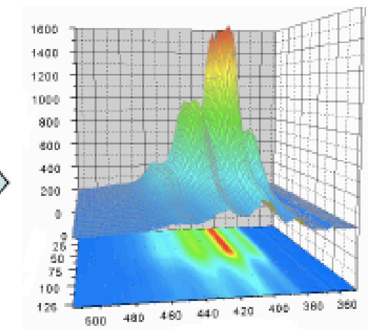
Why RSMs?

- To create synthetic representations of your numerical model in order to shorten optimization computational time



- To interpolate Experimental Data and then optimize empirical models





- To visualize relationships between input variables and output variables / objectives / constraints

$$Out = F(x, y)$$