Advanced Integrate with Ansys optiSLang and Mechanical Software

Ansys

Powering Innovation That Drives Human Advancement

Sensitivity Study and Optimization Theoretical Background

Release 2024 R1

Please note:

- These training materials were developed and tested in Ansys Release 2024 R1. Although they are expected to behave similarly in later releases, this has not been tested and is not guaranteed.
- The screen images included with these training materials may vary from the visual appearance of a local software session.

Agenda

Session	Slide Set	Time	Topic
1	0	5’	Agenda
	1	25’	Introduction to Ansys optiSLang
		10’	Ansys optiSLang in the Ansys Learning Hub – Find your Examples
		15’	Q/A
	2	**30’**	**Sensitivity Study and Optimization – Theoretical Background**
2	3	75’	Hands-on – Process Integration, Sensitivity Study and Postprocessing Steel Hook – optiSLang inside Workbench
		15’	Q/A
3	4	40’	Hands-on – Optimization Steel Hook – optiSLang inside Workbench
	5	20’	Robust Design Optimization – Theoretical Background
	6	40’	Hands-on – Robustness Evaluation Steel Hook – optiSLang inside Workbench
		15’	Q/A

Theoretical Background

Sensitivity Study

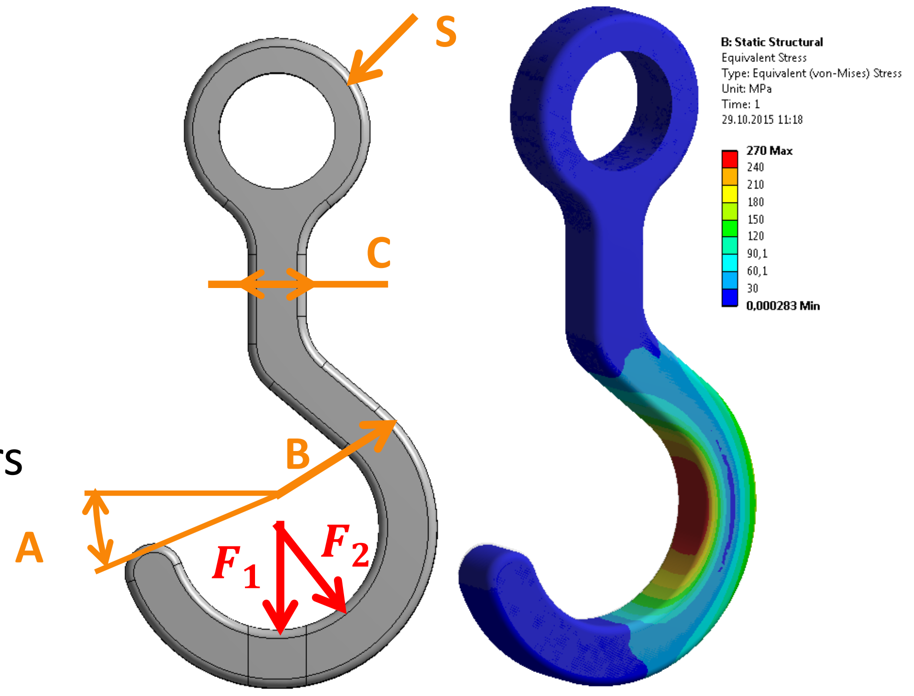
Parametrization

What are Parameters and Responses?

- For variation analyses it is necessary to register Parameters and Responses of the simulation model

Input / Parameters:

- Geometrical Parameters
  e.g. A, B, C
- Load Parameters
  e.g. $\boldsymbol{F_1}$, $\boldsymbol{F_2}$
- Material model Parameters
  e.g. Young´s modulus, Yield stress
- Scattering Parameters
  e.g. A, B, $\boldsymbol{F_1}$, S



Output / Responses:

- Scalar
  e.g. Maximum stress, Mass, Cost
- Vectors, Signals, Curves
  e.g. Force over Displacement
- Matrices
  e.g. 2D and 3D Field data, like stress at every node

Input and Response Variables

- Scalar design variables with continuous, discrete and binary resolution and real, integer or string type
- Scattering variables with continuous resolution
- Scalar responses with continuous resolution
- Vector responses with continuous resolution having variable length
- Signal responses having variable length and several channels

Value type	Resolution	Range		Range plot
REAL	Continuous	8	10	
STRING	Nominal discrete	steel; wood; aluminium		No order
REAL	Ordinal discrete (by index)	125; 150; 350		
REAL	Discrete by value	1.8; 2.2; 3.5; 7.3		

	Type	Mean	Std. Dev.	CoV
	ORMAL	1	0.02	2 %
	ORMAL	20	1	5 %
	NORMAL	0.02	0.002	10 %
	NORMAL	10	1	10 %

Design of Experiments

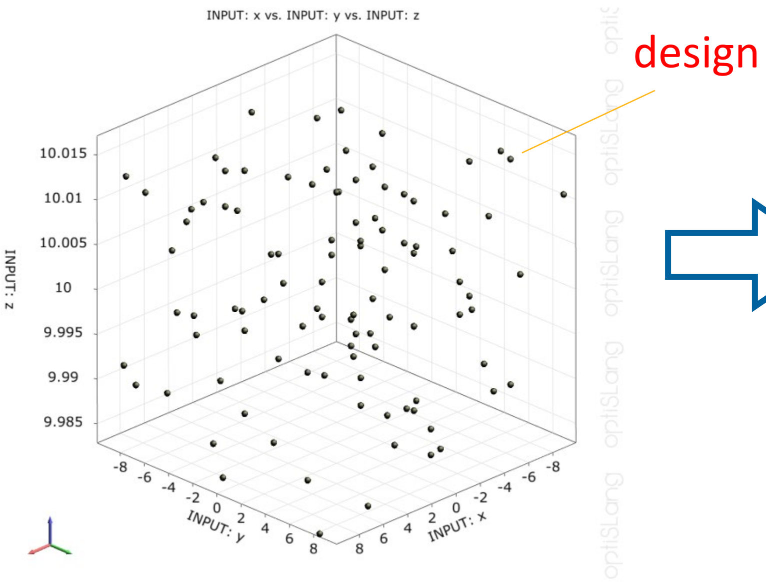
Scanning the Design Space

- A minimum number of designs should cover the entire input space optimally
- Avoid clustering or “white space” and unwanted input correlations
- For each parameter set (“design”) the outputs are calculated or measured

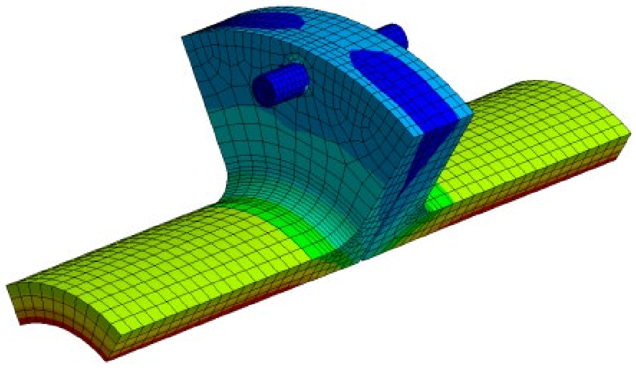
Inputs

$$\left.\begin{matrix} X_1 \\ X_2 \\ \vdots \\ X_k \end{matrix}\right\}$$

Design of Experiments



Model evaluation



Outputs

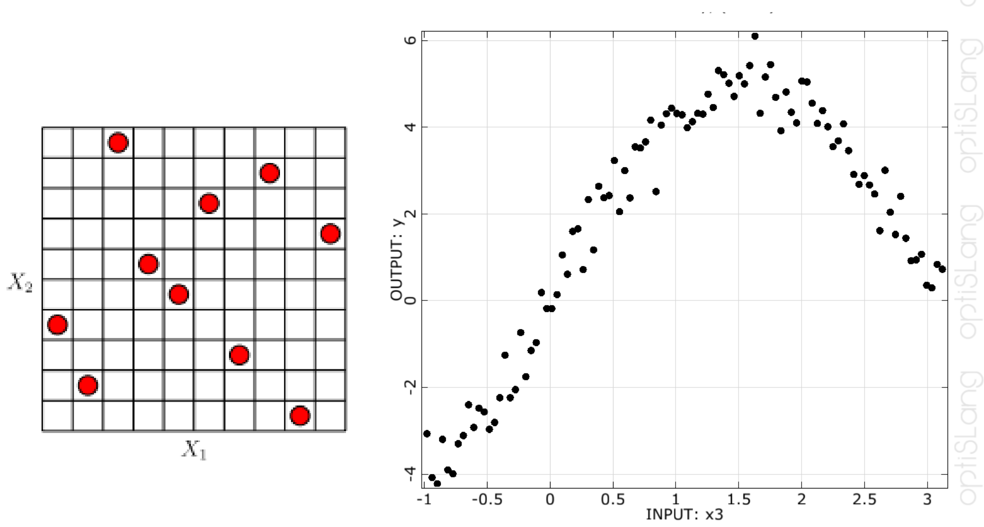
$$\left\{\begin{matrix} Y_1 \\ Y_2 \\ \vdots \\ Y_m \end{matrix}\right.$$

Why do we prefer Stochastic Sampling ?

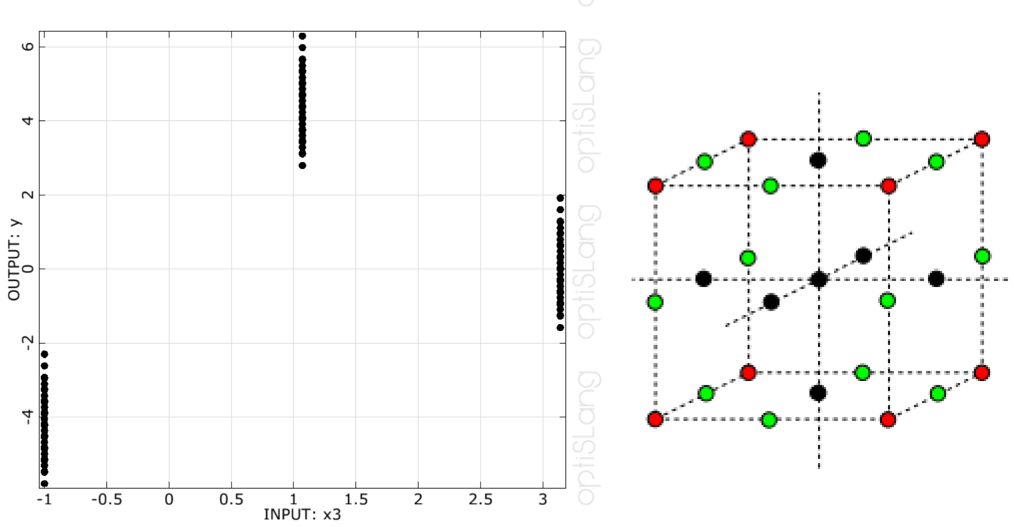
- Deterministic DoE can often consider 2-3 levels for each variable only
- LHS has always *N* levels for each variable

→ If we reduced the variable space by removing unimportant variables, deterministic DoE schemes lose the information of these variables, but with LHS this is not the case

- Example: 4 minor and 1 major important input variables:



LHS, 100 samples



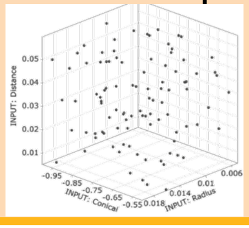
Full factorial, 243 designs

MOP – Metamodel of Optimal Prognosis

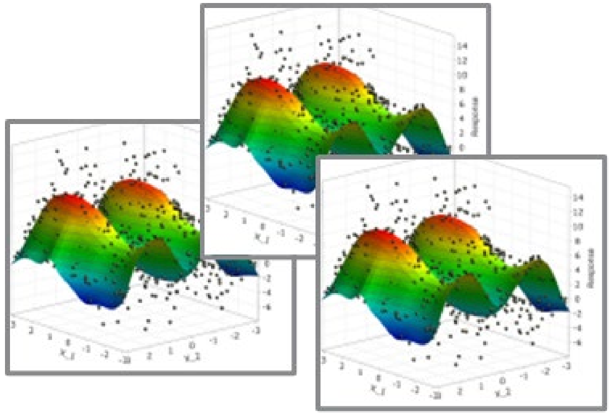
Metamodel of Optimal Prognosis (MOP)

- Objective measure of **prognosis quality**
- Determination of
  - **Relevant parameter subspace**
  - **Optimal approximation model**
- Approximation of solver output by fast surrogate model **without over-fitting**
- Evaluation of **variable sensitivities**

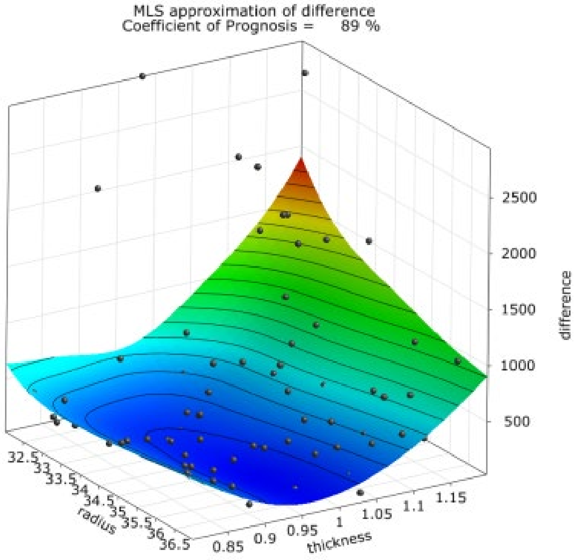
Investigate each response based on DoE sampling



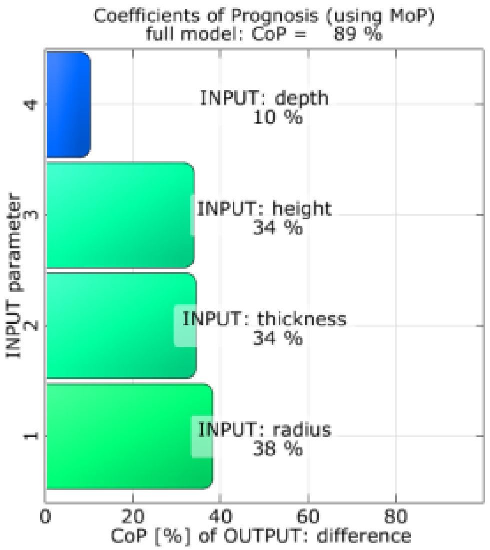
Generate competing metamodels



Calculate forecast quality using CoP for each model



The winner is:
… **MOP**



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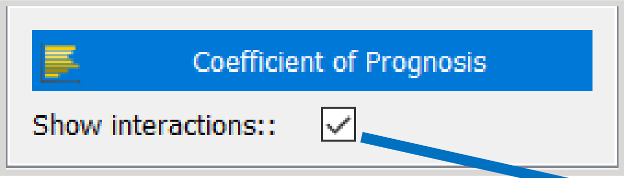
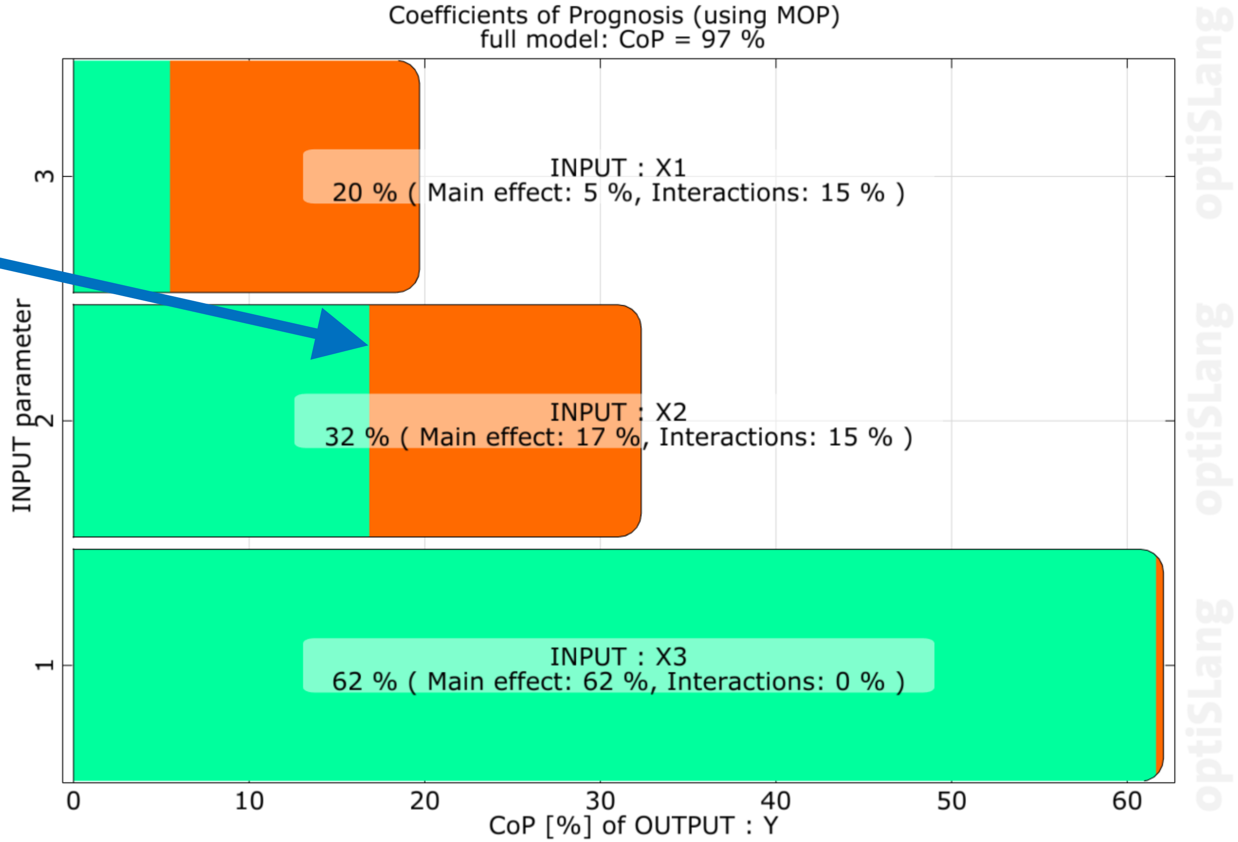
MOP – Sensitivity Indices

- CoP matrix and bar chart provide variance-based **main** and **total effect** sensitivity indices
- Main effect and interaction estimate of each input parameter enables to quantify how a variable contribute to a response, by itself or by interactions with others

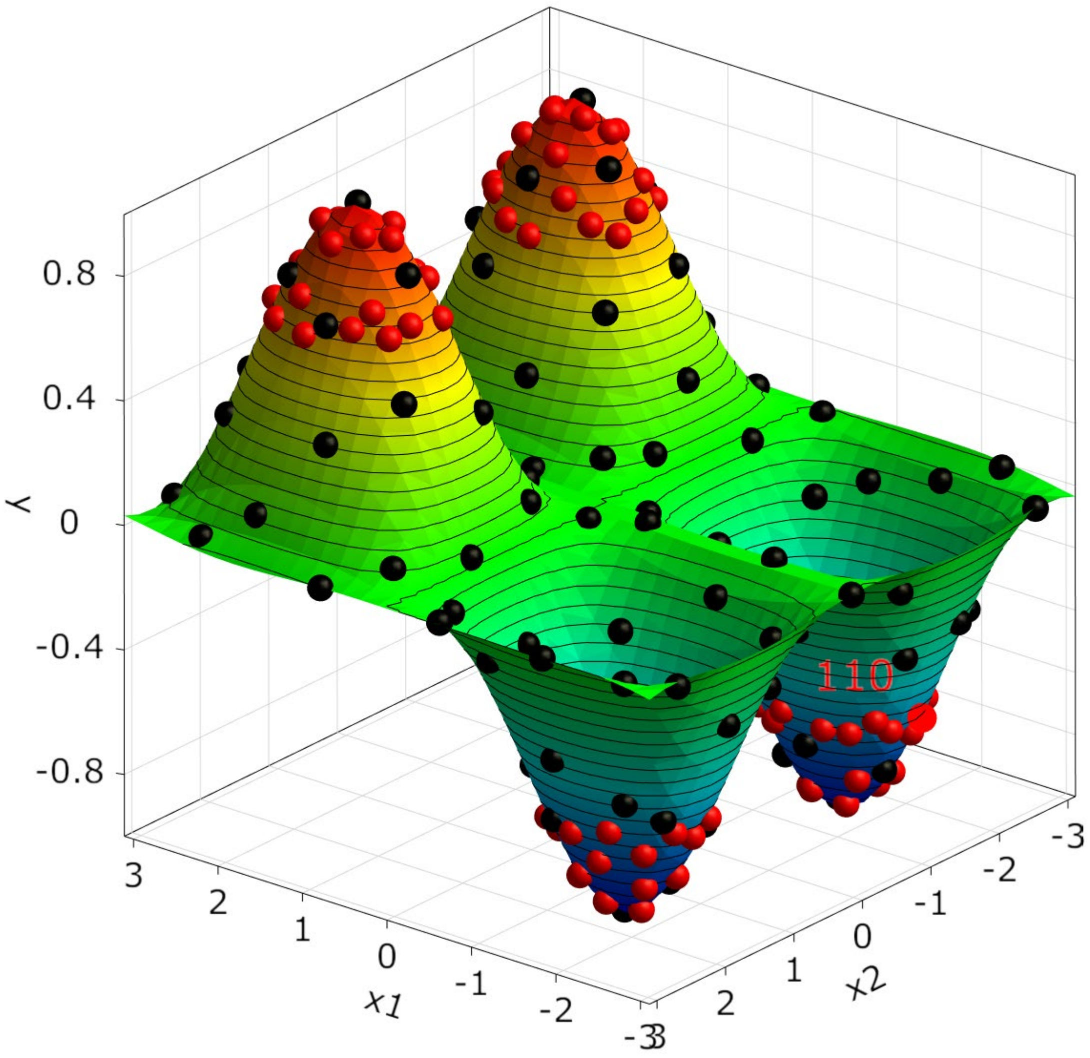




Adaptive MOP

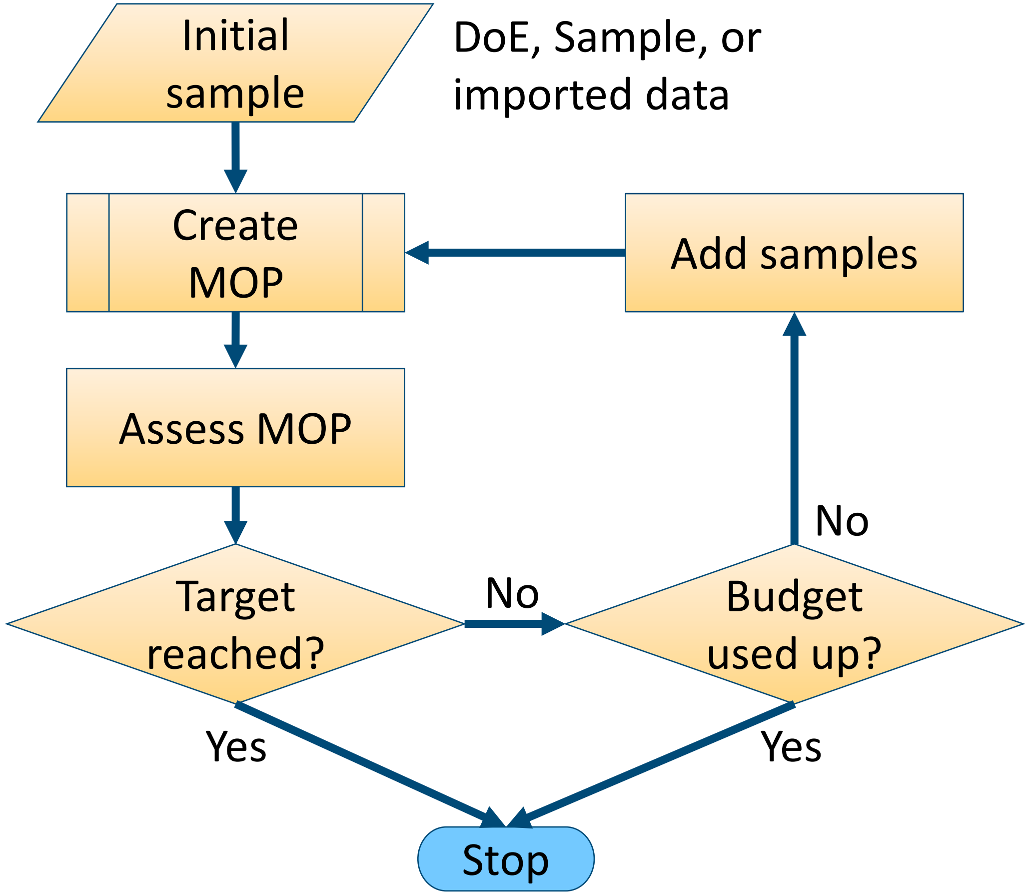
Adaptive Metamodel of Optimal Prognosis - AMOP

- **Iterative procedure**
  - Initial sampling
  - Building metamodel
  - Automatic improvement by adding samples
- **Global parameter scan**
  with advanced and space-filling
  Latin Hypercube Sampling
- **Local refinement** considering
  - Sample density
  - Local approximation errors
  - Optimization criteria



Adaptive Metamodel of Optimal Prognosis – AMOP

- Automatic adaptation of an initial sampling set
- **Global search**
  - Initial DoE or Sample
  - Add samples in entire range of parameters
  - Until target CoP is reached
- **Local refinement**
  - Initial DoE or Sample
  - Pointwise refinement of supports grid considering:
    - Local CoP,
    - Sample density and/or Optimization criteria



Optimization

Theoretical Background

Single-Objective Optimization

Optimization: Mathematical Problem Statement

Design variables

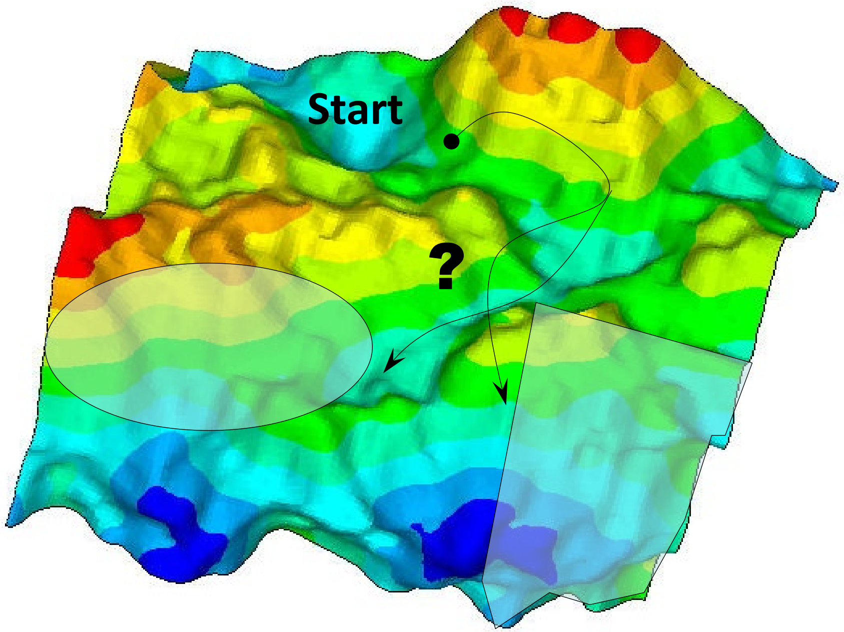
- Parameters defining the design space (continuous, discrete, binary)

Objective function

- Function $f(x)$ has to be minimized
- A unique global minimum may not exist

Constraints

- Restrict the design space by equality or inequality constraints

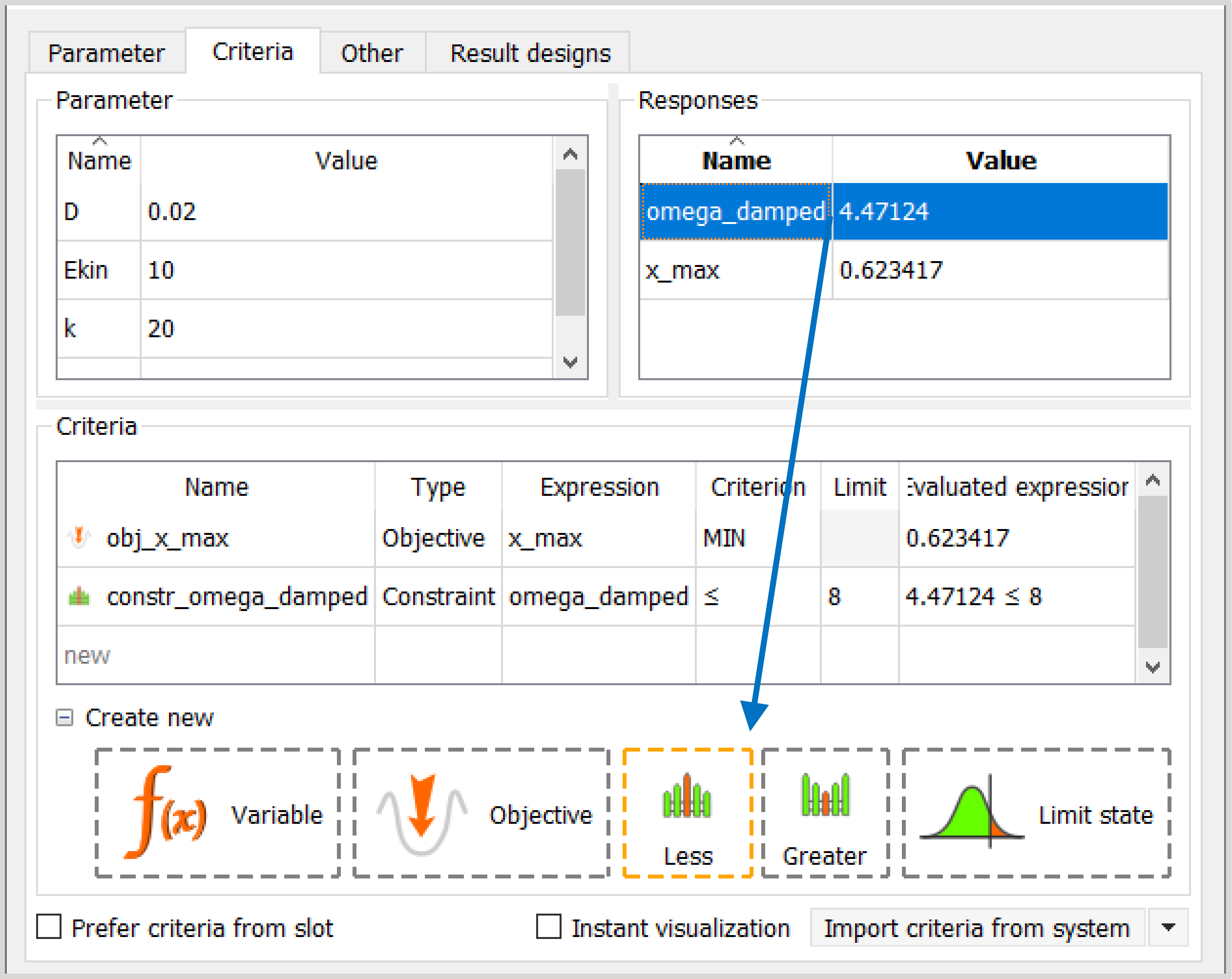


Scaling

- Most optimizers require constraints and objectives to be of the same order of magnitude (apply scaling based on Sensitivity study results)

Definition of the Optimization Task in optiSLang

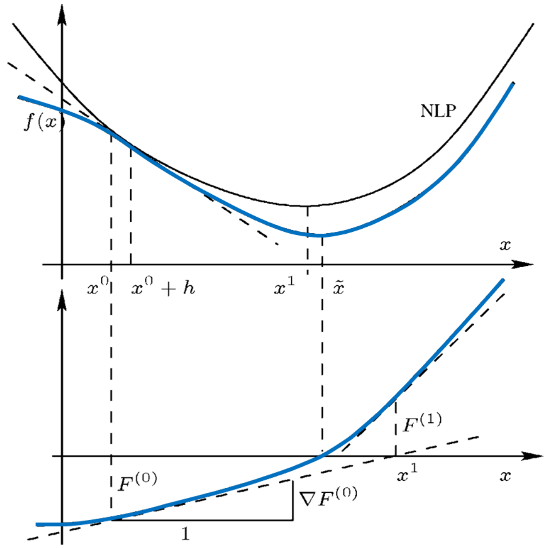
- All design parameters, responses and auxiliary variables can be used within mathematical expressions to define objective and constraint functions
- Internal calculator can be applied
- Minimization and maximization tasks are possible
- Only inequality constraints are possible
- The positive (feasible) case is formulated as constraint
- Criteria can be exported to a csv or json file, or imported from csv, json, omdb, or existing system, or passed in via slot



optiSLang Optimization Algorithms: Concepts

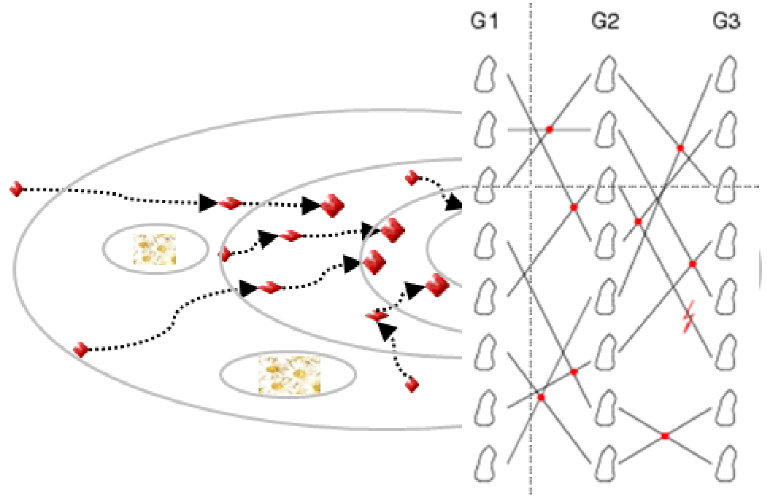
Gradient-Based Methods

- Go downhill
- In the context of black-box solver → gradients are computed by discrete points



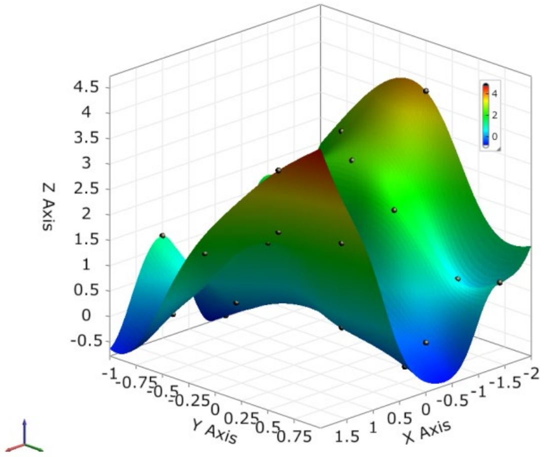
Nature-Inspired Optimization

- Inspiration sources: evolution, swarm motion, thermodynamics, social insects
- Operators such as mutation, recombination, selection, propagation, etc.



Surrogate-based Optimization

- DoE and response surface fit
- Scanned area is adapted (shift and zoom)



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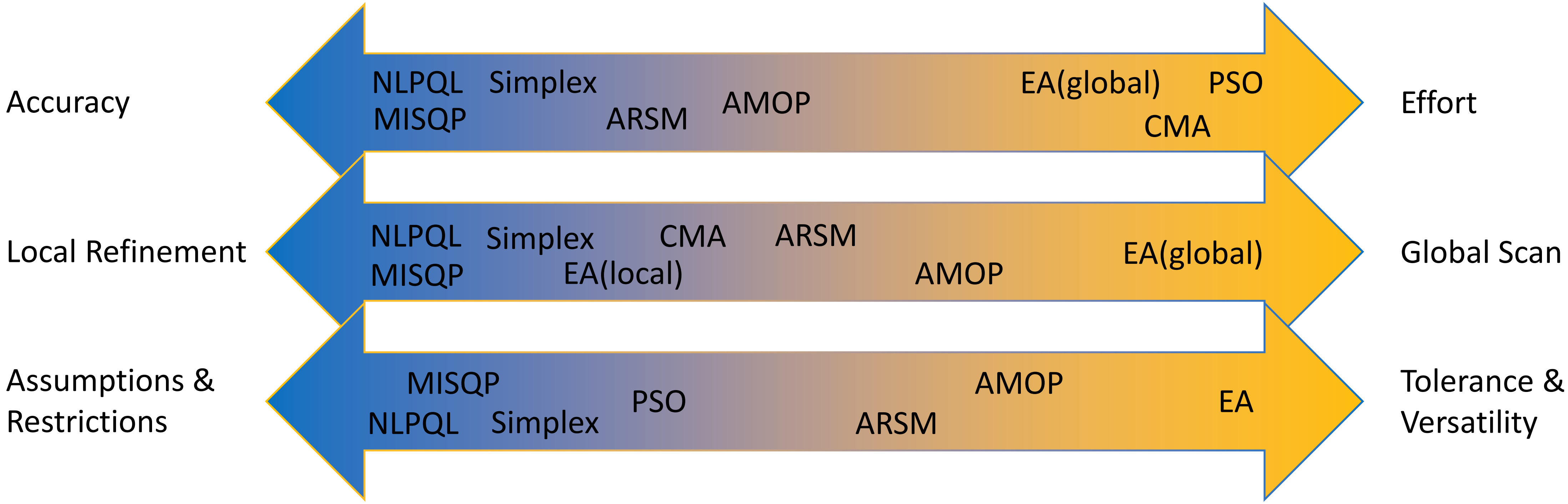
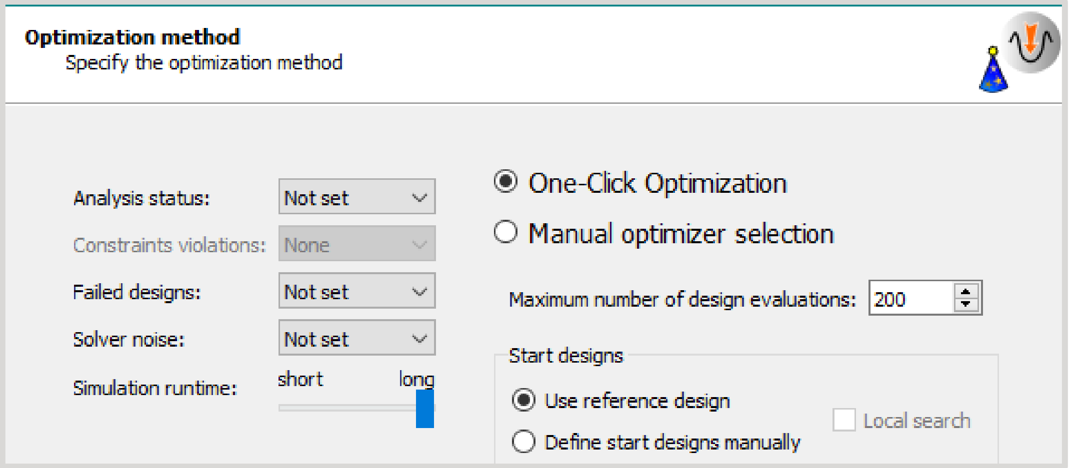
optiSLang Optimization Algorithms: Conclusions



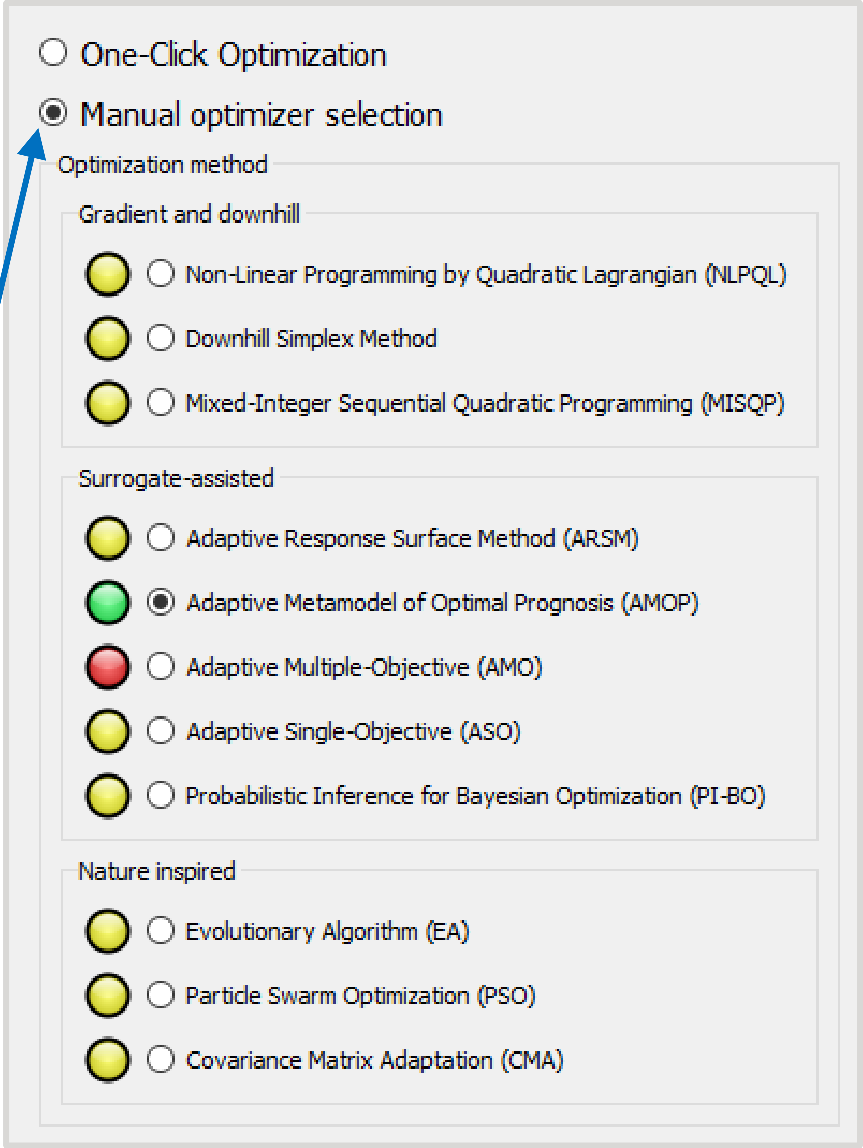
- optiSLang offers a variety of optimization algorithms
- For each class of problem, there is one best algorithm
- A compromise of accuracy and versatility vs. computational effort has to be found
- Insights from the sensitivity analysis help to take the best decision

Default Optimizer: OCO

- Motivation: easy to use and robust algorithm with just one setting: computation budget
- Since release 2023R1 the default algorithm in the Optimization Wizard

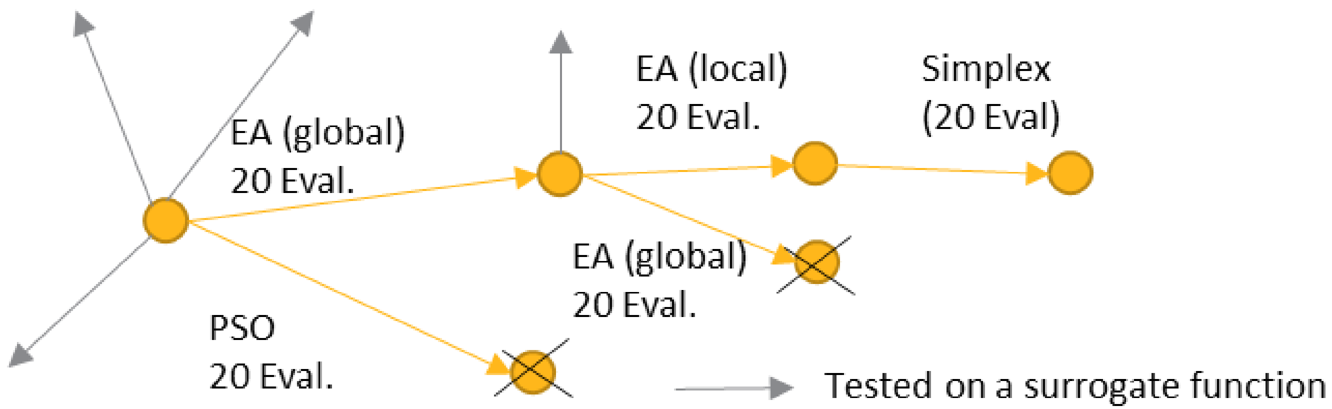


- If manual optimizer is selected, all other algorithms can be chosen manually, with recommendation by a traffic light system

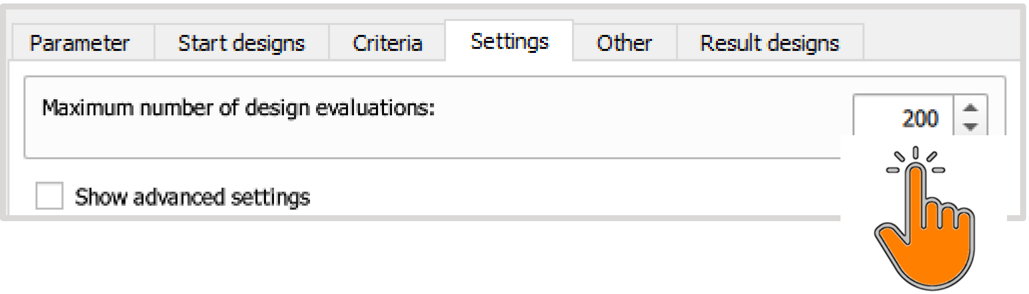


One-Click Optimization (OCO)

- Concept: put several algorithms to the contest
- Internal AI selects automatically and dynamically the most suitable algorithm
- Combine high-fidelity (CAE solver) and low-fidelity models (MOP) to speed up convergence
- MOP/CoP analysis used to reduce dimension
- Suitable for single and multi objective optimization tasks



One setting: computation budget



Multi-Objective Optimization

The Multi-Objective Optimization Task

- Several optimization criteria are formulated in terms of the input variables

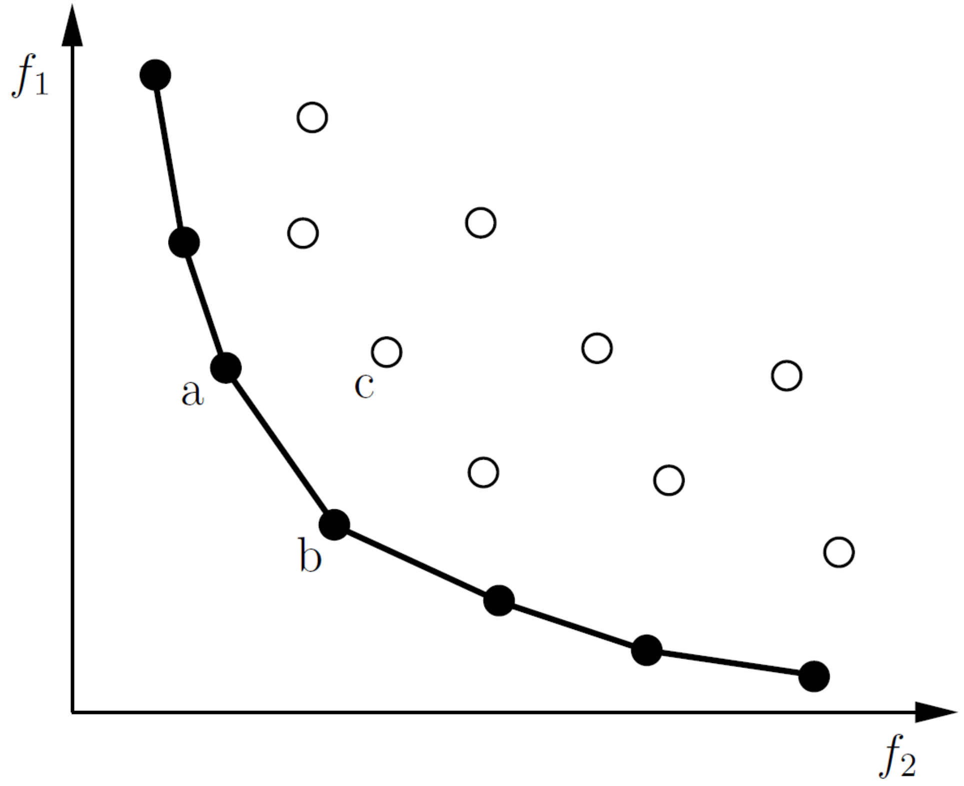
$$f_1(\mathbf{x}) \rightarrow \min$$
$$\vdots$$
$$f_n(\mathbf{x}) \rightarrow \min$$

- Uncountable set of solutions, if criteria are contradicting

→ Balanced compromise is wanted

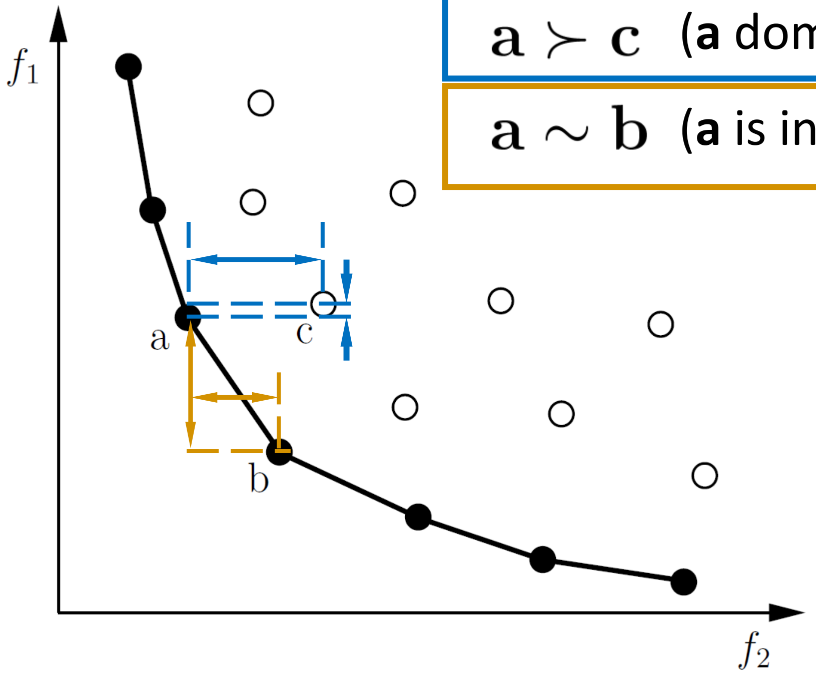
→ Scan of the Pareto-front as decision base

- Constraint restrictions are possible



Pareto Optimality

- Solution **a** dominates solution **c** since **a** is better in both objectives
- Solution **a** is indifferent to **b** since each solution is better than the respective other in one objective
- A design is Pareto optimal, if it is not dominated by any other design
- The set of Pareto optimal solutions forms the Pareto front



$\mathbf{a} \succ \mathbf{c}$ (**a** dominates **c**)

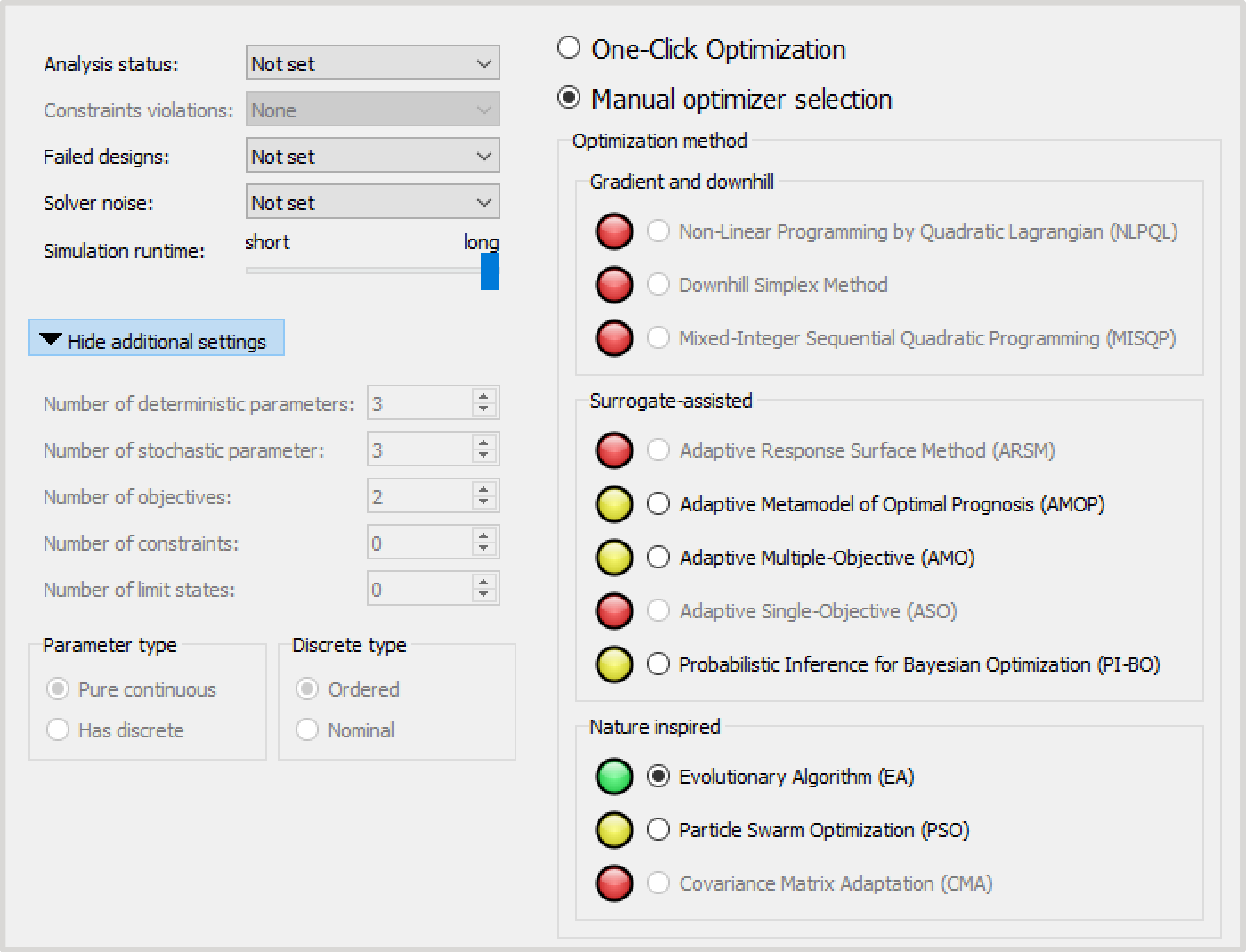
$\mathbf{a} \sim \mathbf{b}$ (**a** is indifferent to **b**)

Pareto Optimization: Requirements

- Convergence: Find a set of solutions close to the Pareto front
- Diversity: Find a set of solutions which represent the Pareto front to a large extent
- Resolution: Aim at an even discretization

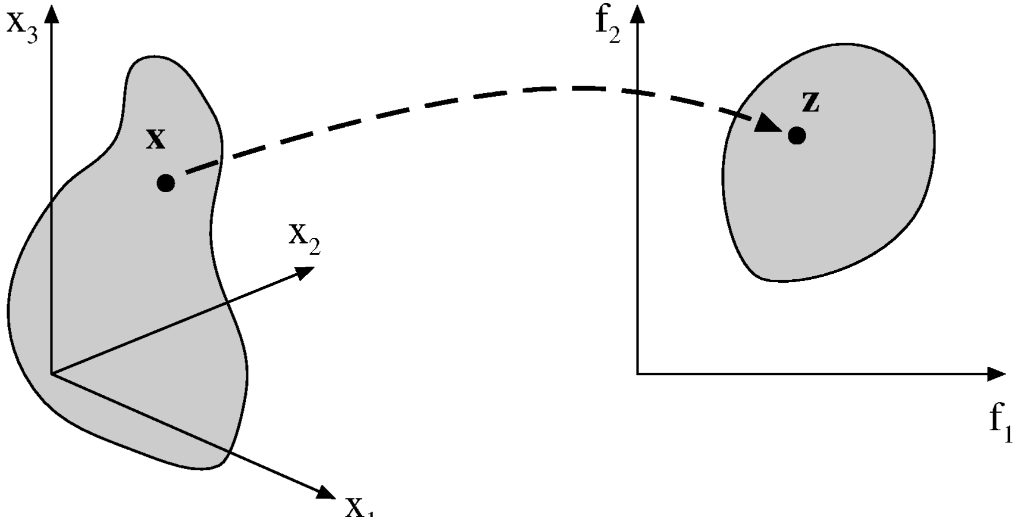
Wizard-based Recommendation for Algorithm Selection

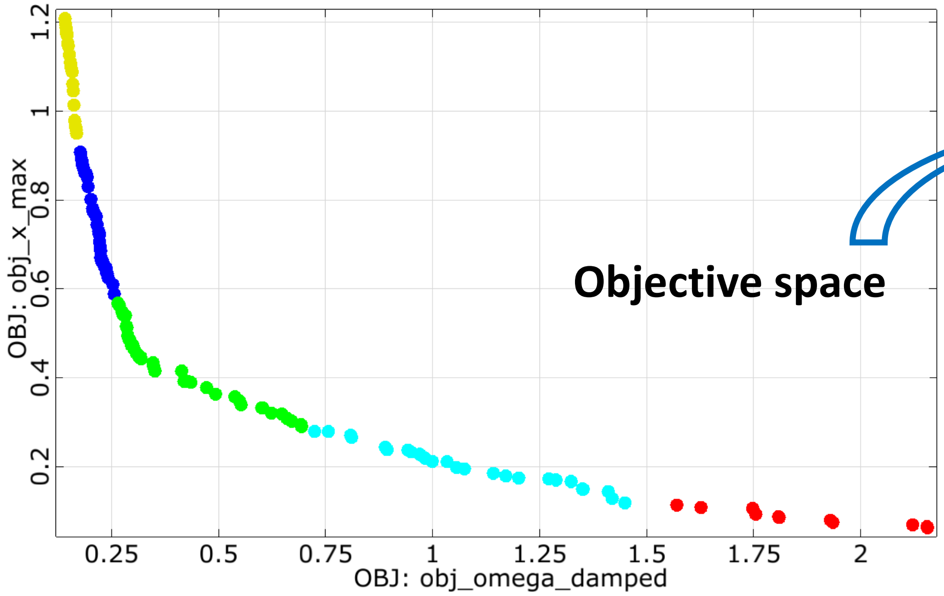
- One-Click Optimizer (with higher budget than for single-objective optimization) is default
- For manual selection, multi-objective optimization with no user defined settings, EA is the recommendation
- Some algorithms are disabled because they are not suitable for multi-objective optimization



The Multi-Objective Optimization Task

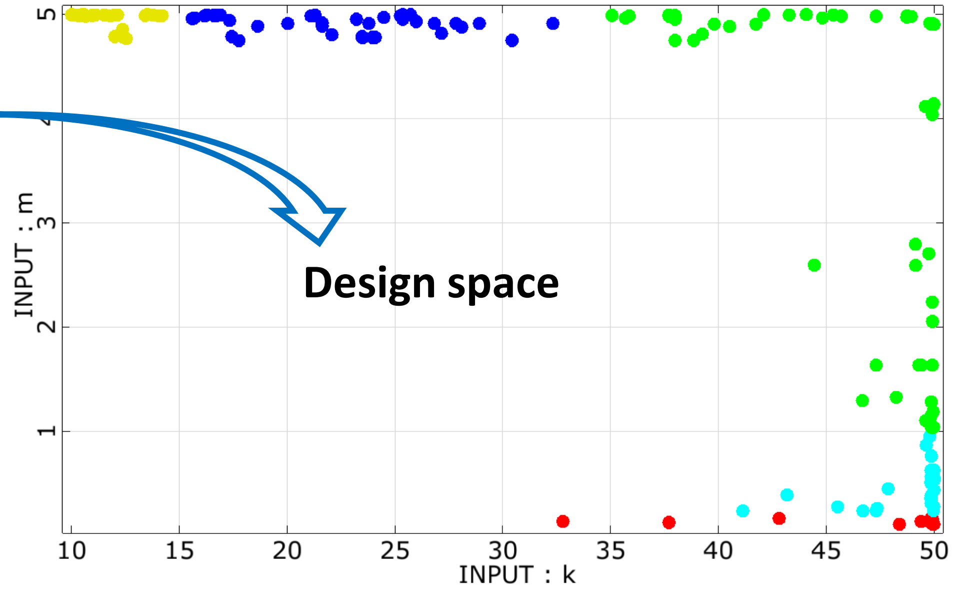
- Infer from design space to objective space





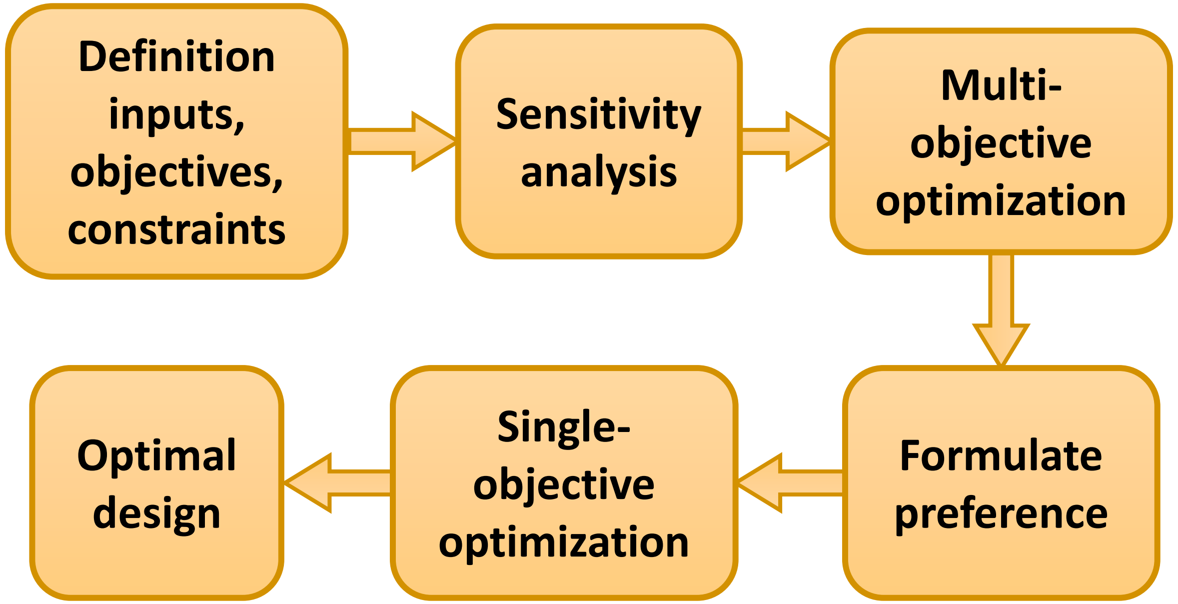
Objective space

Design space



Recommended Workflow for Multiple Objectives

1. Define parameter types and ranges, responses, objectives and constraints
2. Perform a sensitivity analysis using DOE and MOP to detect conflicting objectives, get information about failed or infeasible design regions, get suitable start population
3. Perform a multi-objective optimization for all conflicting objectives
4. Formulate preferences (e.g., constraints, reduced range)
5. Run single-objective optimization
6. Get your optimal design



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