Laboratory for Product Development and Lightweight Design
TUM School of Engineering and Design
Technical University of Munich

A Tutorial on Using the SSO Toolbox

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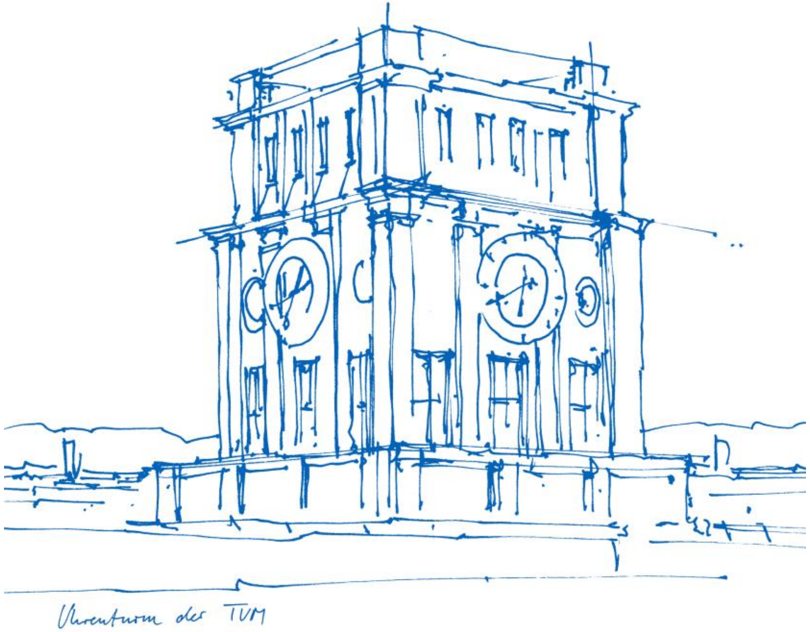
Garching, 02.09.2024



General Content

1. Defining a System Response Function
2. Finding an Optimal Box-shaped Solution Space (and visualization – 3D plot; selective design space projection)
3. Using Surrogate Modeling (with Active Learning)
4. Stacking Evaluators (Multi-fidelity simulation, Solution-Compensation Spaces)
5. Interlude: Finding an Optimal Design
6. Interlude: Using Python Bottom-up Mappings
7. Interlude: Performing Batch Analysis
8. Interlude: Requirement Spaces
9. Using Component Solution Space Optimization – Simple Example
10. Using Component Solution Space Optimization – Advanced Example

Getting Started

Code is available on both GitLab and the OneDrive

GitLab Instructions:

- Clone the tutorial project into your PC in a folder of your choosing (Project: Tutorial SSO Toolbox)
  - `git clone https://gitlab.lrz.de/lpl-tum/sso-toolbox-lpl/tutorial-sso-toolbox.git`

OneDrive Instructions:

- Copy the tutorial folder, and create a copy of the sso-toolbox inside of that

Open this folder in MATLAB (or VScode) and run ‘setup_sso_toolbox.m’

- `run('sso-toolbox/setup_sso_toolbox')`

1. Defining a System Response Function

File: `tutorial_01_euclidean_distance_3d`

A system response function must look like this:

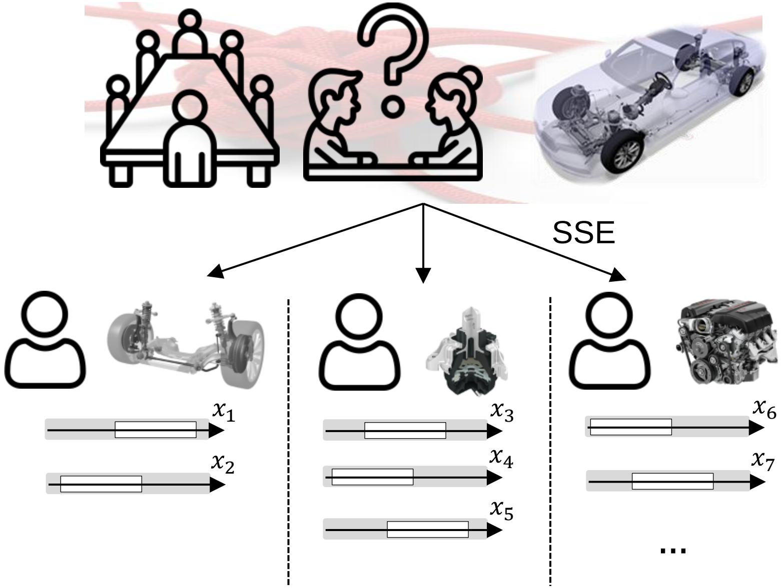
`[performanceMeasure,physicalFeasibilityMeasure,systemOutput] = f(designSample,systemParameter)`

- **`designSample`** : array with all design sample points; each column is a design variable, each row is a different point
- **`performanceMeasure`** : system response (in terms of performance); each column is a performance measure, each row is a different point
- `systemParameter` : constant system parameter (doesn't change with the samples), when applicable
- `physicalFeasibilityMeasure` : physical feasibility of the designs, when applicable
- `systemOutput` : any extra information, when applicable

Task:

Write a function that computes the distances of all given sample points to a center (constant parameter)

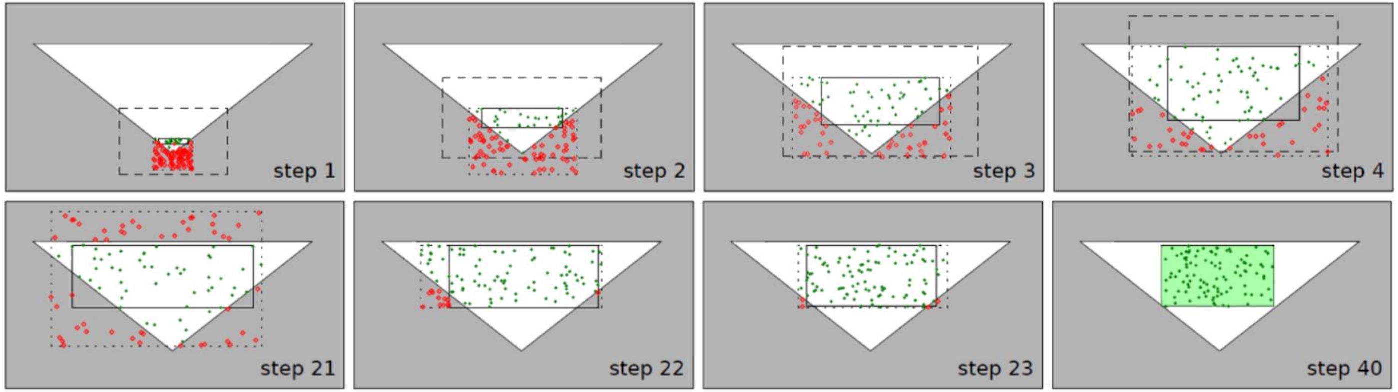
2. Finding an Optimal Box-shaped Solution Space



2. Finding an Optimal Box-shaped Solution Space

Phase I:
Exploration

Phase II:
Consolidation



Classical optimization on Ω_{ds}. Identify one good design $\mathbf{x_0}$.
The first candidate box Ω is constructed at $\mathbf{x_0}$ with zero volume.
Phase I. While $\mu(\Omega)$ is changing:
Modification Step B: Extend candidate box.
Compute Monte Carlo sample in Ω.
Modification Step A: Remove bad sample designs.
Compute Monte Carlo sample in Ω.
Phase II. While $m/N < a_c$:
Modification Step A. Remove bad sample designs.
Compute Monte Carlo sample in Ω.

2. Finding an Optimal Box-shaped Solution Space

File: `tutorial_02_sso_box_sphere`

First, the problem must be setup correctly. For that, a Design Evaluator is needed.

- First setup a Bottom-up Mapping (`BottomUpMappingFunction`).
- Then, use it to create a design evaluator (`DesignEvaluatorBottomUpMapping`).
- Finally, call the box SSO function (`sso_box_stochastic`)

Tip: for more information on functions/classes, you can always use “help <NAME>” or “doc <NAME>”

<u>Task 1:</u>

Run the box-shaped solution space optimization function and obtain the optimal solution space with the following:

- System response: `tutorial_01_euclidean_distance_3d`
- Design Space: $-6 \leq x_1, x_2, x_3 \leq 6$
- Performance Limits: $distance \leq 5$ (center: $[0,0,0]$)
- Initial Design: $[x_1, x_2, x_3] = [3,0,0]$

2. Finding an Optimal Box-shaped Solution Space

File: `tutorial_02_sso_box_sphere`

Visualization tools:

- Boxes in 2D and 3D can be easily plotted using the functions: `plot_design_box_2d`, `plot_design_box_3d`
- Selective Design Space Projection: `plot_selective_design_space_projection`

Common performance metrics can also be automatically plotted: `postprocess_sso_box_stochastic` → `plot_sso_box_stochastic_metrics`

Task 2:

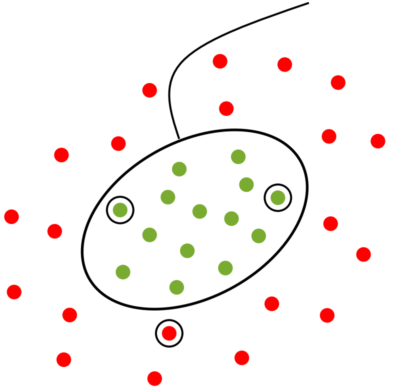
Visualize the solution space box in 3D, and then also use selective design space projection

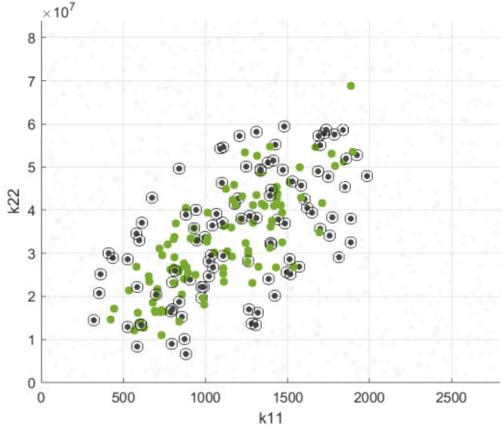
Task 3:

Plot the algorithm performance metrics for this solution

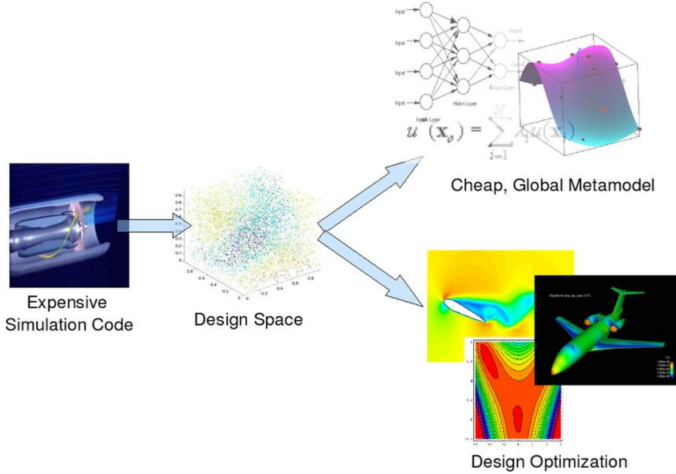
3. Using Surrogate Modeling (with Active Learning)

Decision boundary can be used to select data points during the sampling





From: Lukas Krischer, DokSem #7



Source: https://www.researchgate.net/profile/Tom-Dhaene/publication/265152921/figure/fig1/AS:335678228451328@1457043334234/Surrogate-modeling-versus-Design-Optimization.png

3. Using Surrogate Modeling (with Active Learning)

File: `tutorial_03_surrogate_modeling`

Special class of surrogate modeling for top-down systems design: `DesginFastForwardBase`
Active learning method: `active_learning_model_training`
Visualization of performance metrics: `postprocess_active_learning_model_training` → `plot_active_learning_model_training_metrics`

Task 1:

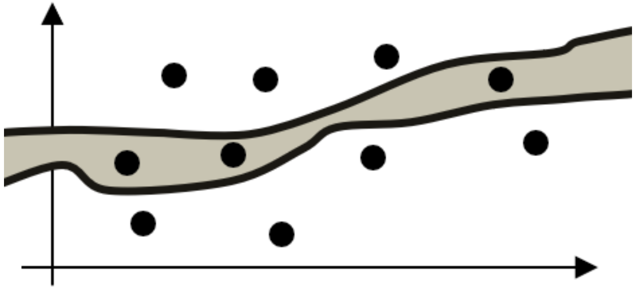
Train a surrogate model for the following problem:

- System response: `tutorial_01_euclidean_distance_3d`
- Design Space: $-6 \leq x_1, x_2, x_3 \leq 6$
- Performance Limits: $2 \leq distance \leq 5$ (center: $[0,0,0]$)

Task 2:

Visualize how the algorithm performance metrics evolved at each iteration.

4.1 Stacking Evaluators – Multifidelity Evaluation



White region: low- and high-fidelity models agree

Gray region: low- and high-fidelity models disagree

4.1 Stacking Evaluators – Multifidelity Evaluation

File: `tutorial_04_1_multifidelity`

Transforming a `DesignFastForwardBase` object to a `DesignEvaluatorBase` object: `DesignEvaluatorFastForward`
Estimating region of uncertainty: `design_fast_forward_find_uncertainty_score`

Task 1:
Train a surrogate model for the following problem:

- System response: `tutorial_01_euclidean_distance_3d`
- Design Space: $-6 \leq x_1, x_2, x_3 \leq 6$
- Performance Limits: $distance \leq 5$ (center: $[0,0,0]$)
- Maximum number of iterations: 1
- Number of samples to be evaluated per iteration: 20

Task 2:
Estimate the region of uncertainty.

4.1 Stacking Evaluators – Multifidelity Evaluation

File: `tutorial_04_1_multifidelity`

Setting up a multi-fidelity evaluator: `DesignEvaluatorMultiFidelity`

Task 3:

Solve a box SSO problem using the Multifidelity evaluator with the following additional considerations:

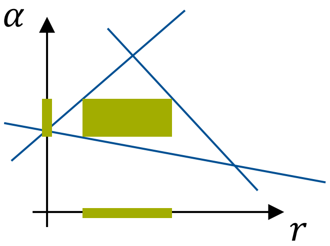
- Initial Design: $[x_1, x_2, x_3] = [3{,}0{,}0]$

4.2 Stacking Evaluators – Solution-compensation Spaces

Solution Spaces:

$$\min_{[\alpha_l,\alpha_u,r_l,r_u]} -\mu(\Omega)$$

$$\text{s.t. } g(r,\alpha) \leq 0$$



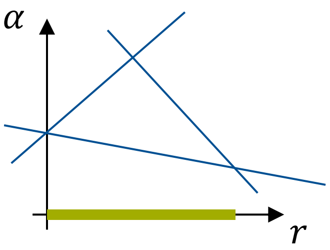
Solution Compensation Spaces:

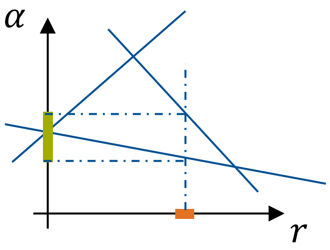
$$\min_{[r_l,r_u]} -\mu(\Omega_\mathrm{a})$$

$$\text{s.t. } \forall x_a \in \Omega_a \; \exists \; x_b \in \Omega_b$$

early decision variables (limited controllability, PFD): sensor characteristics, $x_a = r$

late decision variables (controllable): sensor positionings, $x_b = \alpha$





From: Nicola Barthelmes, DokSem #5

4.2 Stacking Evaluators – Solution-compensation Spaces

File: `tutorial_04_2_compensation`

Setting up an evaluator for solution-compensation spaces: `DesignEvaluatorCompensation`

Task:

Solve a box SCSO problem with the following considerations:

- System response: `tutorial_01_euclidean_distance_3d`
- Design Space: $-6 \leq x_1, x_2, x_3 \leq 6$
- Performance Limits: $distance \leq 5$ (center: $[0,0,0]$)
- Initial Design: $[x_1, x_2, x_3] = [3,0,0]$
- A-space: $[x_1, x_2]$; B-space: x_3

5. Interlude: Finding an Optimal Design

File: `tutorial_05_point_based_optimal_design`

Special optimization functions:

- `design_optimize_quantities_of_interest`
- `design_optimize_performance_score`

Task:

Find optimal designs for the 2D car crash problem: one with the best acceleration, another with the best score.

6. Interlude: Using Python Bottom-up Mappings

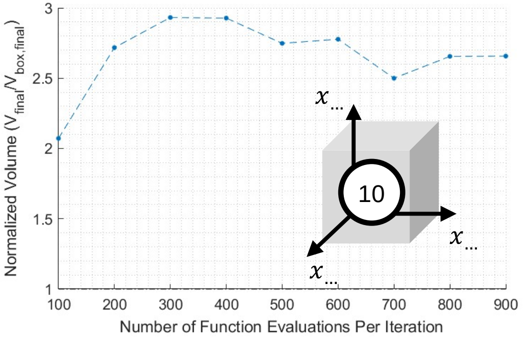
File: `tutorial_06_python_bottom_up_mapping`

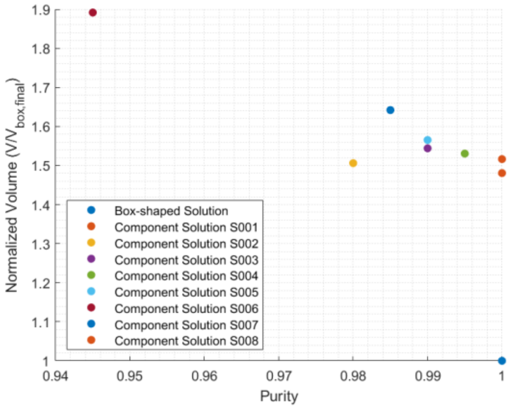
Setting up a bottom-up mapping that uses Python code for its system response: `BottomUpMappingPython`

Task:

- Find the optimal box for the 2D car crash problem using the MATLAB function `car_crash_2d`
- Find the optimal box for the 2D car crash problem using the Python function `car_crash_2d_python.py`

7. Interlude: Performing Batch Analysis





ID	ReferenceID	Number Samples Per Iteration	Growth Rate	Tolerance Purity Consolidation
S001	-	200	0.2	1
S002	S001	100	0.2	1
S003	S001	300	0.2	1
S004	S001	200	0.1	1
S005	S001	200	0.3	1
S006	S001	200	0.2	0.85
S007	S001	200	0.2	1
S008	S001	200	0.2	1

7. Interlude: Performing Batch Analysis

File: `tutorial_07_batch_analysis`

Reading a table: `batch_analysis_read_table`

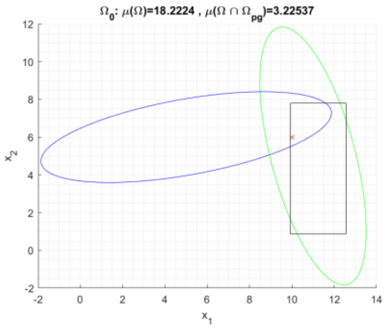
Batch SSO analysis: `batch_sso_stochastic_analysis`

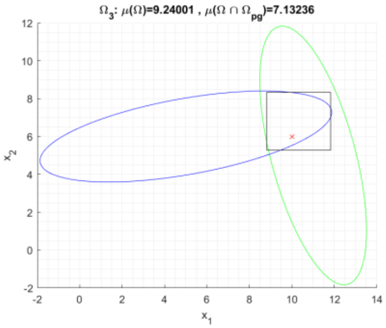
Task:

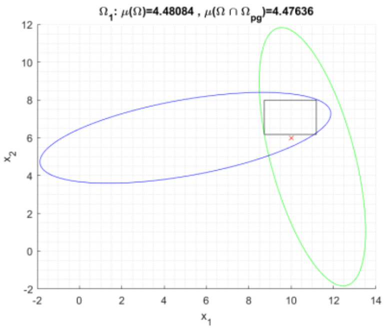
Perform a batch analysis for the following problem:

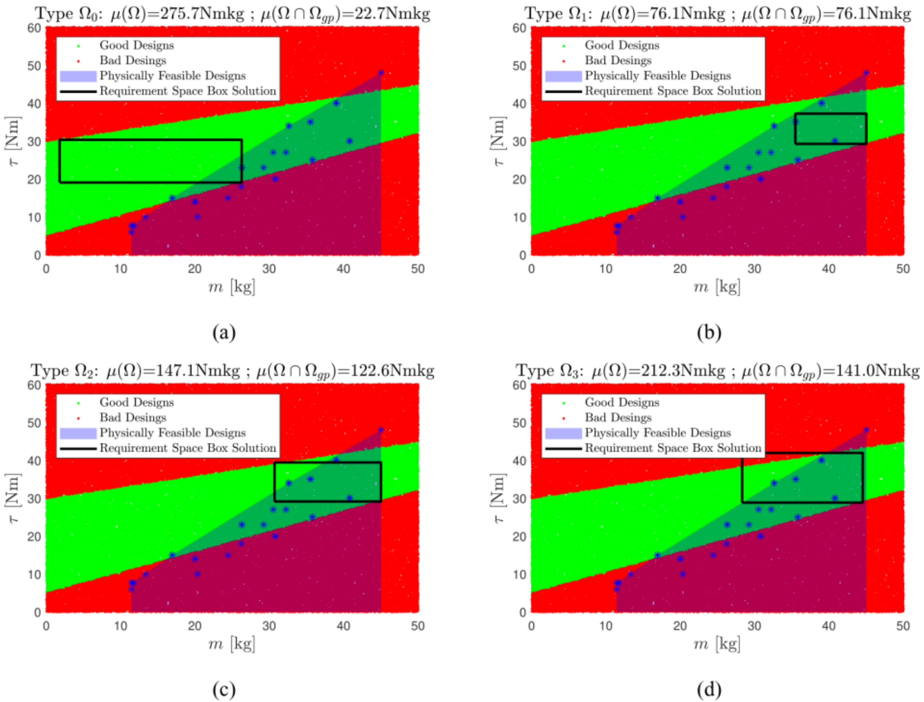
- System response: `tutorial_01_euclidean_distance_3d`
- Design Space: $-6 \leq x_1, x_2, x_3 \leq 6$
- Performance Limits: $distance \leq 5$ (center: $[0,0,0]$)
- Initial Design: $[x_1, x_2, x_3] = [3,0,0]$
- Batch options: 'BatchTestHollowSphere.xlsx'

8. Interlude: Requirement Spaces









8. Interlude: Requirement Spaces

File: `tutorial_08_requirement_spaces`

Important option:

- `'RequirementSpacesType’` (in `sso_stochastic_options`)
- `'PhysicalFeasibilityUpperLimit'` (in `DesignEvaluatorBottomUpMapping`)

Task:

Solve the following requirement spaces problem:

- System response: `two_ellipses_requirement_space`
- Design Space: $-2 \leq x_1 \leq 14\,; -2 \leq x_2 \leq 12$
- Performance Limit: $\text{ellipsenorm} \leq 1$
- Physical Feasibility Limit: $\text{ellipsenorm} \leq 1$
- Initial Design: $[x_1, x_2\,] = [10{,}6]$
- Number of evaluations per iteration: 200
- Apply leanness condition only at the end

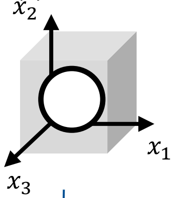
9. Component Solution Space Optimization – Simple Example

Example: Sphere

Components:

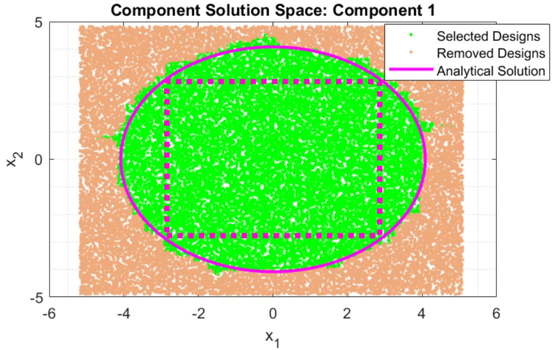
$\boldsymbol{x}_{(1)} = [x_1, x_2]$

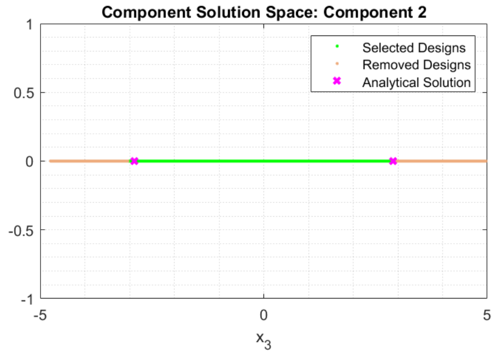
$\boldsymbol{x}_{(2)} = [x_3]$



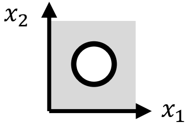
Stochastic Algorithm

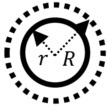
Corner Box Removal





Analytical Solution





$r = R\sqrt{\frac{2}{3}}$

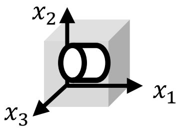
$l = \frac{2R}{\sqrt{3}}$

Solution Box Area:

$$A_b = l_b^2 = \left(\frac{2R}{\sqrt{3}}\right)^2 = R^2\,\frac{4}{3}$$

Component Solution Space Area:

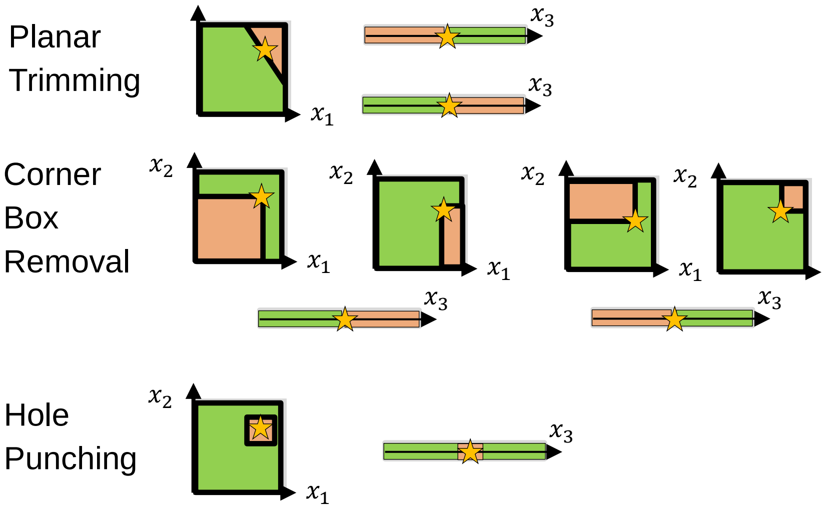
$$A_c = \pi r_c^2 = \pi\left(R\sqrt{\frac{2}{3}}\right)^2 = R^2\,\frac{2\pi}{3}$$

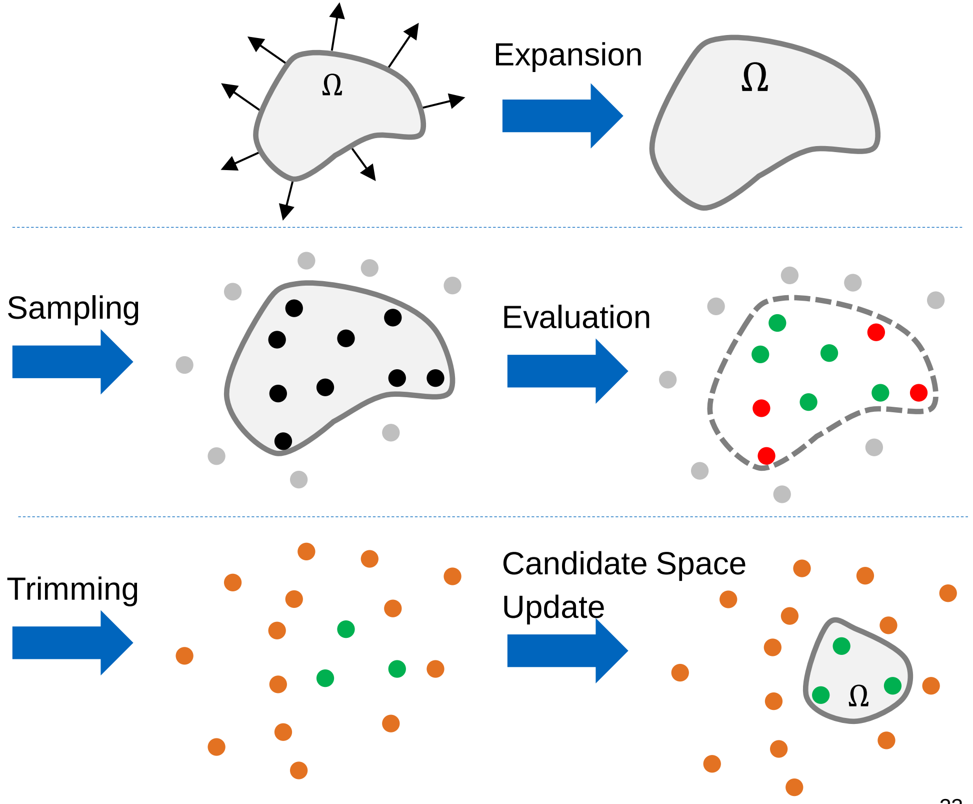


<u>~57% increase in area</u>

9. Component Solution Space Optimization – Simple Example

- Candidate space operations:
  - Expand (given a growth rate g)
  - Identify x_{sample} as inside or outside
  - Be updated given samples x_{in}, x_{out}





9. Component Solution Space Optimization – Simple Example

File: `tutorial_09_component_solution_space_simple`

Candidate Space Definition: `CandidateSpaceBase`

Trimming Methods: `component_trimming_method_<NAME>`

Component SSO function: `sso_component_stochastic`

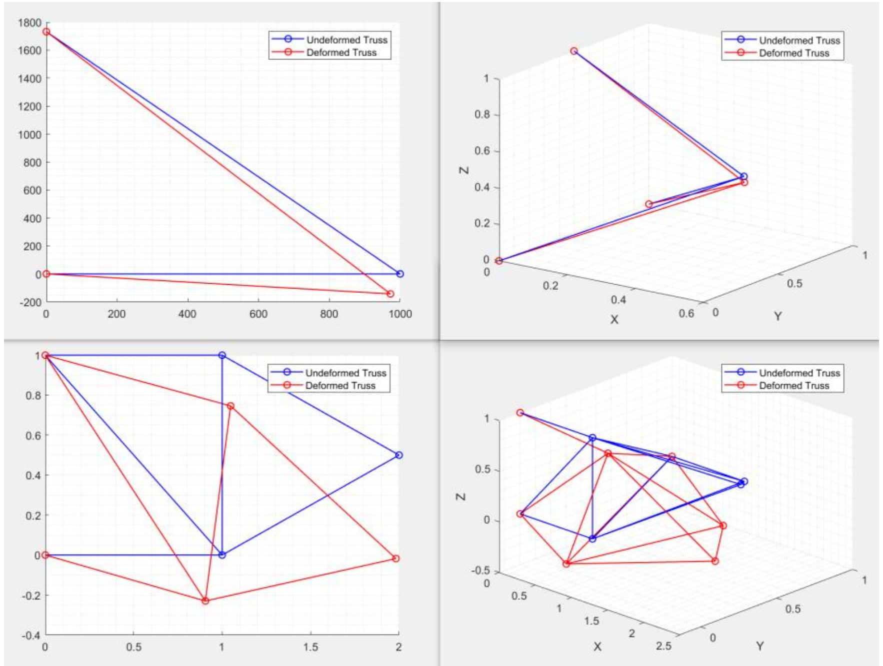
Performance metrics: `postprocess_sso_component_stochastic` → `plot_sso_component_stochastic_metrics`

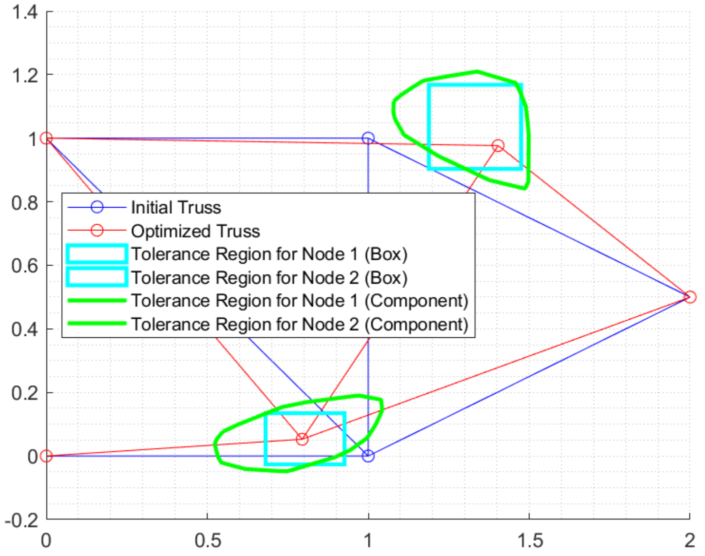
Task:

Solve the following requirement spaces problem:

- System response: `tutorial_01_euclidean_distance_3d`
- Design Space: $-6 \leq x_1, x_2, x_3 \leq 6$
- Performance Limits: $distance \leq 5$ (center: $[0,0,0]$)
- Initial Design: $[x_1, x_2, x_3] = [3,0,0]$
- Number of samples per iteration: 300

10. Component Solution Space Optimization – Advanced





10. Component Solution Space Optimization – Advanced

File: `tutorial_10_component_solution_space_advanced`

Options to use:

- Growth rate: 0.1
- Number of exploration/consolidation iterations: 30
- Number of evaluations per iteration: 300

Tasks:

- Setup the bottom-up mapping
- Find the optimum design with minimum displacement
- Find the optimum solution space box starting from the optimum design and having as performance limit a 10% tolerance from the optimum displacement
- Find the optimum component solution space under the same conditions
- Visualize both box and component solution space in the same plot to compare
- Plot performance metrics for each

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Thank you for your attention!

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LPL

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