Uncertainty and optimization: a coupled problem for scenario analyses

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MINISTERIO DE CIENCIA E INNOVACIÓN
Ciemat Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas

Outline

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- Introduction
- Evolutionary strategies\DE
- Scenario description
- Results
- Uncertainties
- Conclusions

Skarbeli, AV, Álvarez-Velarde, F, Bécares, V. Optimization under uncertainty for robust fuel cycle analyses. *Int J Energy Res*. 2021; 45: 6139– 6151. doi: 10.1002/er.6236

Introduction

Nuclear fuel cycle simulators are very powerful tools for the study and analysis of the different nuclear fuel cycles

Each facility is modelled according to a series of input parameters, so when the simulation is completed, results in terms of mass, isotopic content, radiotoxicity, costs... can be obtained

Nevertheless from the strategic point of view the inverse problem is presented:

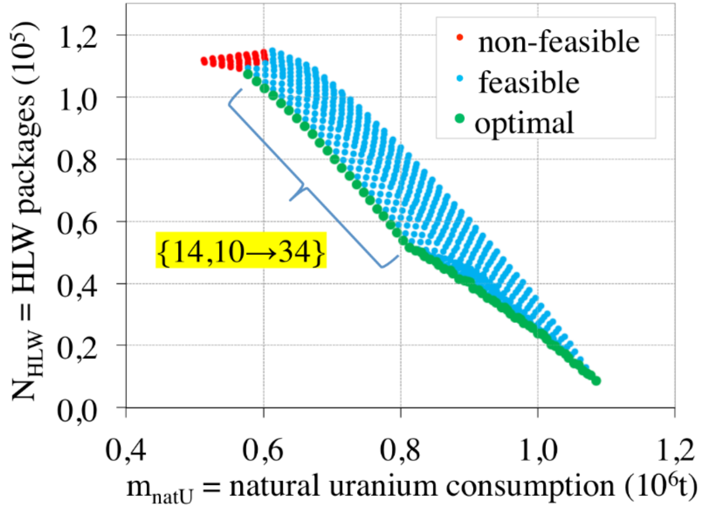
- The results of the cycle are set (cost minimization, inventories stabilization, …)
- But it is not clear which configuration will fulfil the requirements

Optimization problem!

Introduction

Nuclear fuel cycle optimization is a multiobjective problem

- There are unlimited criteria for the optimization
  - Volume of TRU inventories
  - U_{nat} requirements
  - Fuel cycle costs
  - Proliferation risk
  - ….
- And in general, no scenario will optimize all of them simultaneously
  - Trade-off between improving one objective and degrading the others: Pareto Front



Freynet, D. et al. "Multiobjective optimization for nuclear fleet evolution scenarios using COSI". In: EPJ Nuclear Sciences & Technologies 2 (2016), p. 9. doi:10.1051/epjn/e2015-50066-7

It also usually contains constrains or restrictions (e.g., the demanded fabrication mass cannot exceed the stocks)

Introduction

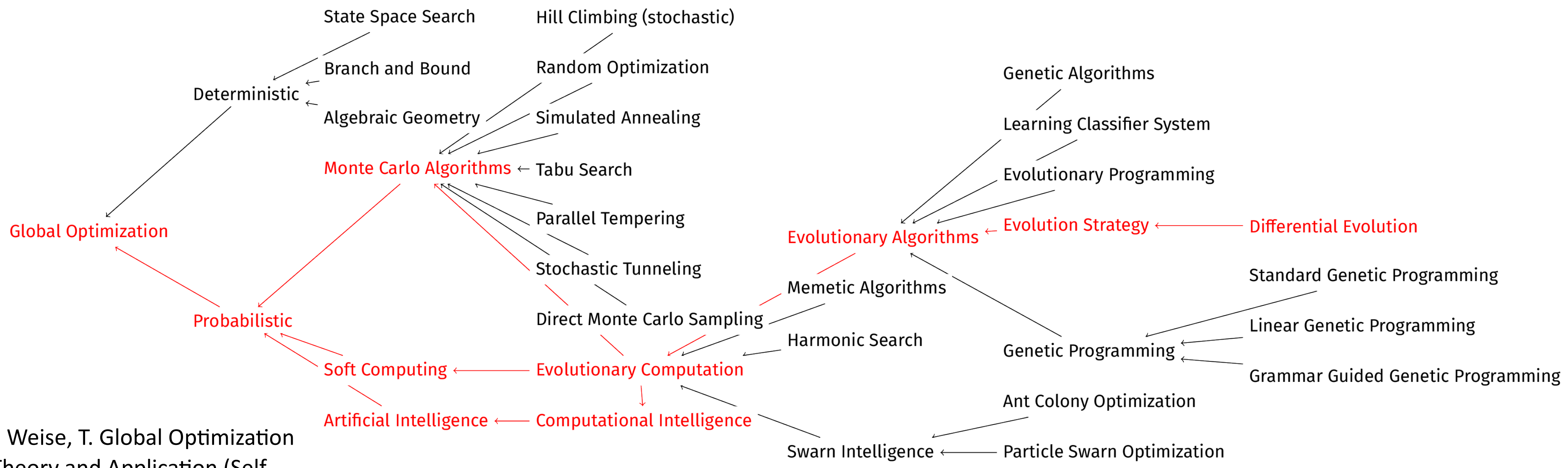
Properties of the problem

- Black-box funtion
  - Unknown structure
  - Non-differentiable
- Global optimization

Characteristics of the simulator & environment

(TR_EVOL system on CIEMAT’s clusters)

- Fast execution speed (~min)
- Parallel executions (up to 300)



Adapted from Weise, T. Global Optimization Algorithms - Theory and Application (Self-Published), June 2009. http://www.it-weise.de

No free lunch theorem

Evolutionary strategies\DE

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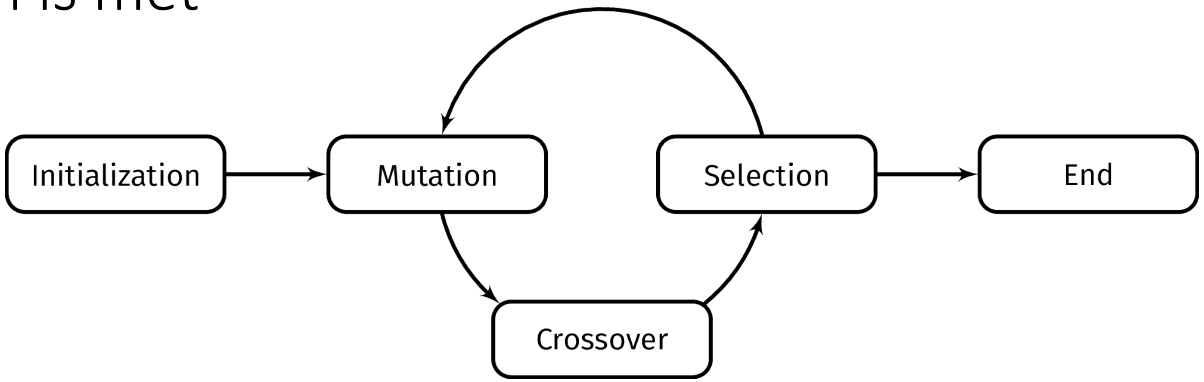
These families of algorithms are based on generating a set of candidate solutions which are iteratively updated until convergence criterion is met



Differential Evolution (DE)

- Extremely simple algorithm
- Three key operations: Mutation, Crossover/Recombination and Selection
  - For each generation, the Mutation and Crossover operators produce a new set of candidate solutions (agents) applying linear combination and permutations to the best ones
  - These candidate solutions are only accepted if they improve the existing ones

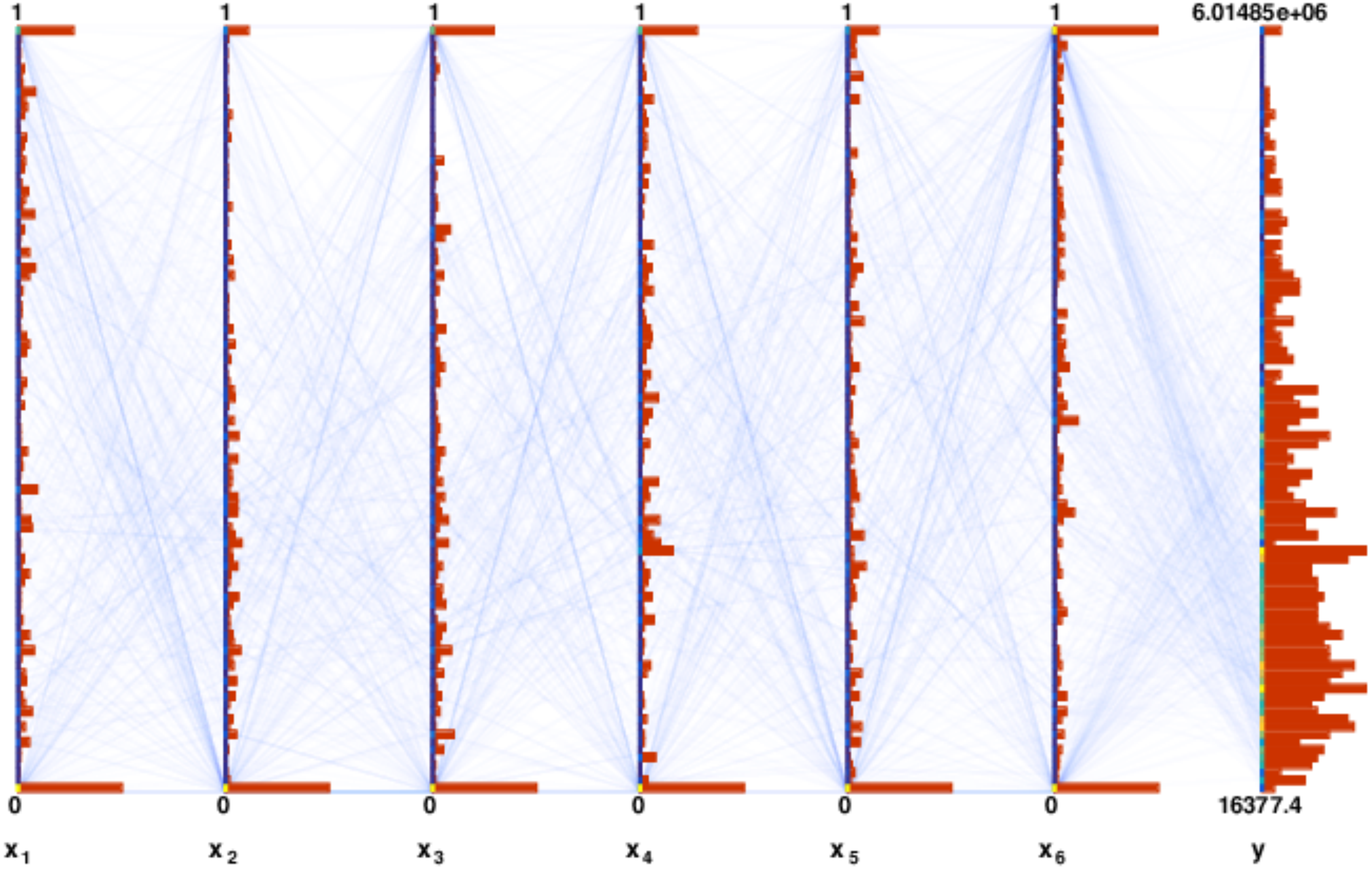
Storn, R. and Price, K. Differential Evolution - A simple and efficient adaptive scheme for global optimization over continuous spaces. Tech. rep. TR-95-012. Berlekey: International Computer Science Institute, 1995

Storn, R. and Price, K. “Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces”. In: Journal of Global Optimization 11.4 (1997), pp. 341–359. doi: 10.1023/a:1008202821328

Evolutionary strategies\DE

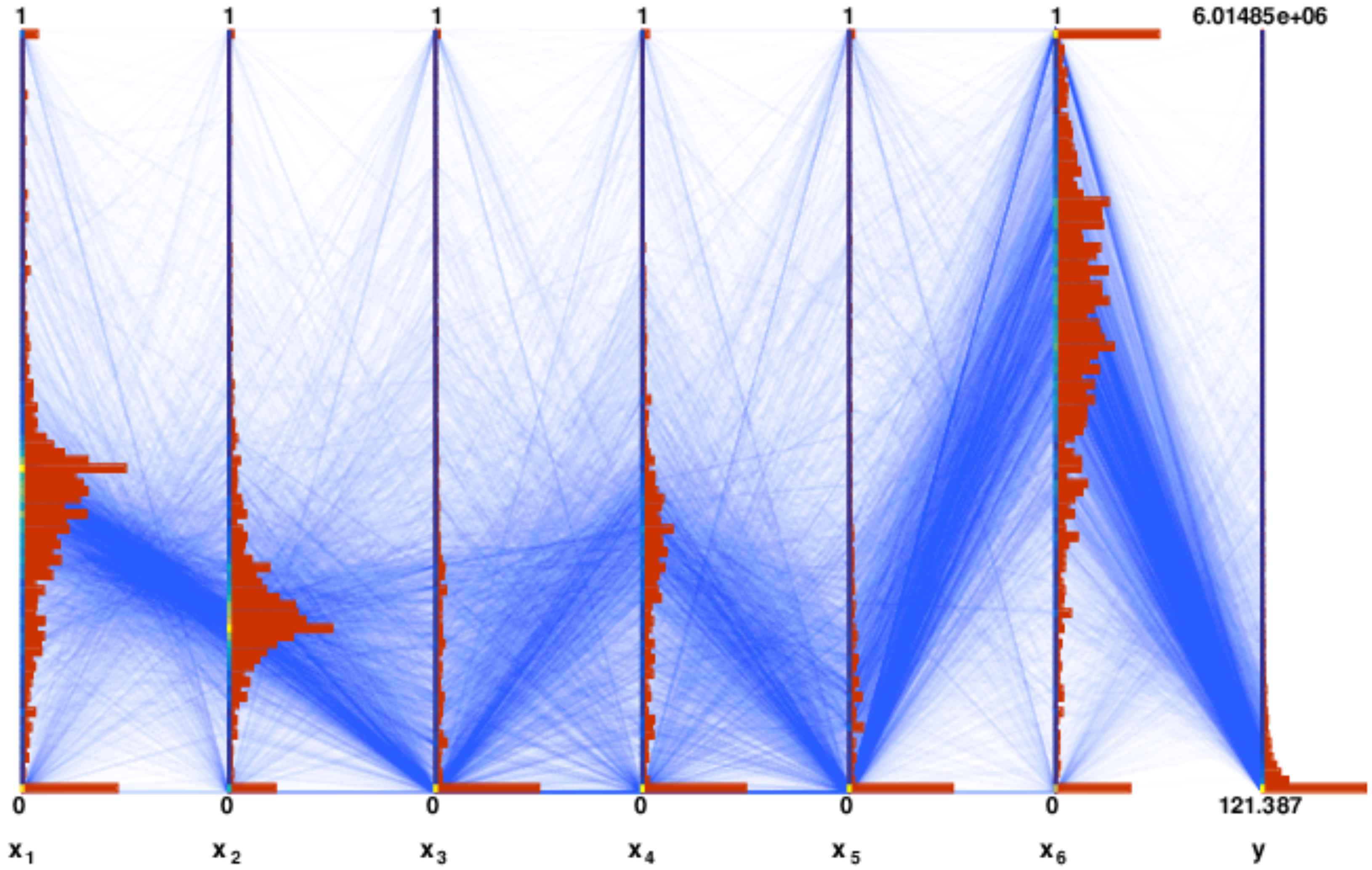
Test function $y = f(x_1, x_2, x_3, x_4, x_5, x_6)$

10 generations



Evolutionary strategies\DE

100 generations



Evolutionary strategies\DE

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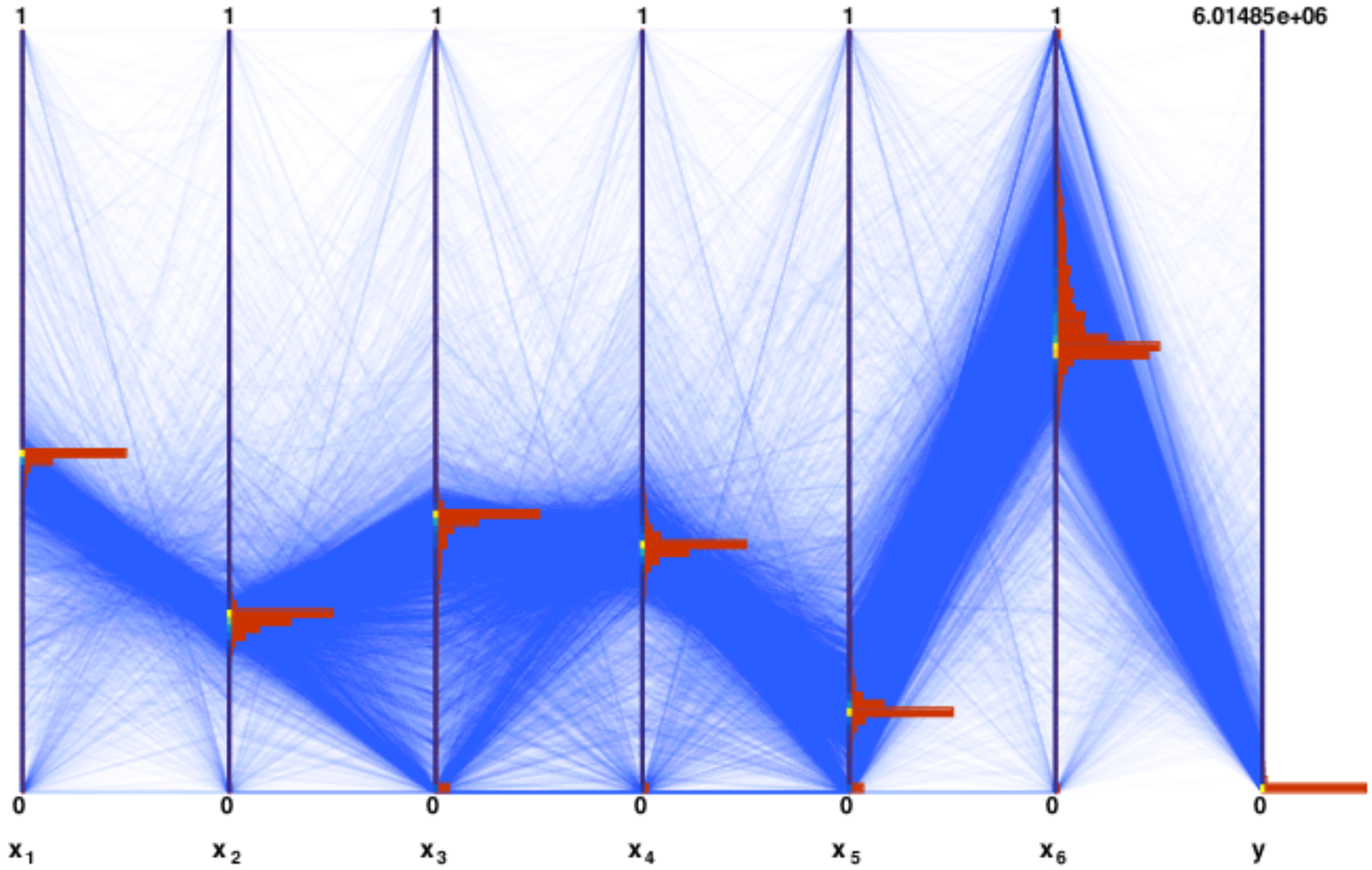
Final convergence



Evolutionary strategies\DE

Multiobjective optimization

- DEMO extension (Differential Evolution for Multiobjective Optimization): the selection is replaced with a mechanism based on Pareto ranking

Robič, T. and Filipič, B. “DEMO: Differential Evolution for Multiobjective Optimization”. In: Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2005, pp. 520–533. doi: 10.1007/978-3-540-31880-4_36

Constrained optimization

$$\min_{\boldsymbol{x}\in R^d} f(\boldsymbol{x}) \text{ subject to } \begin{cases} g_i(\boldsymbol{x}) < 0 \text{ for } 0 \le i \le r \\ h_j(\boldsymbol{x}) = 0 \text{ for } 0 \le j \le s \end{cases} \quad \Rightarrow \quad \phi(\boldsymbol{x}) \coloneqq \sum_i \max\left(0, g_i(\boldsymbol{x})\right)^p + \sum_j \left\|h_j(\boldsymbol{x})\right\|^p$$

- ε level comparison: The candidates with the lower penalties are preferred

Takahama, T. and Sakai, S. “Constrained Optimization by ε Constrained Particle Swarm Optimizer with ε-level Control”. In: Advances in Soft Computing. Springer Berlin Heidelberg, 2005, pp. 1019–1029. doi: 10.1007/3-540-32391-0_105

Scenario description

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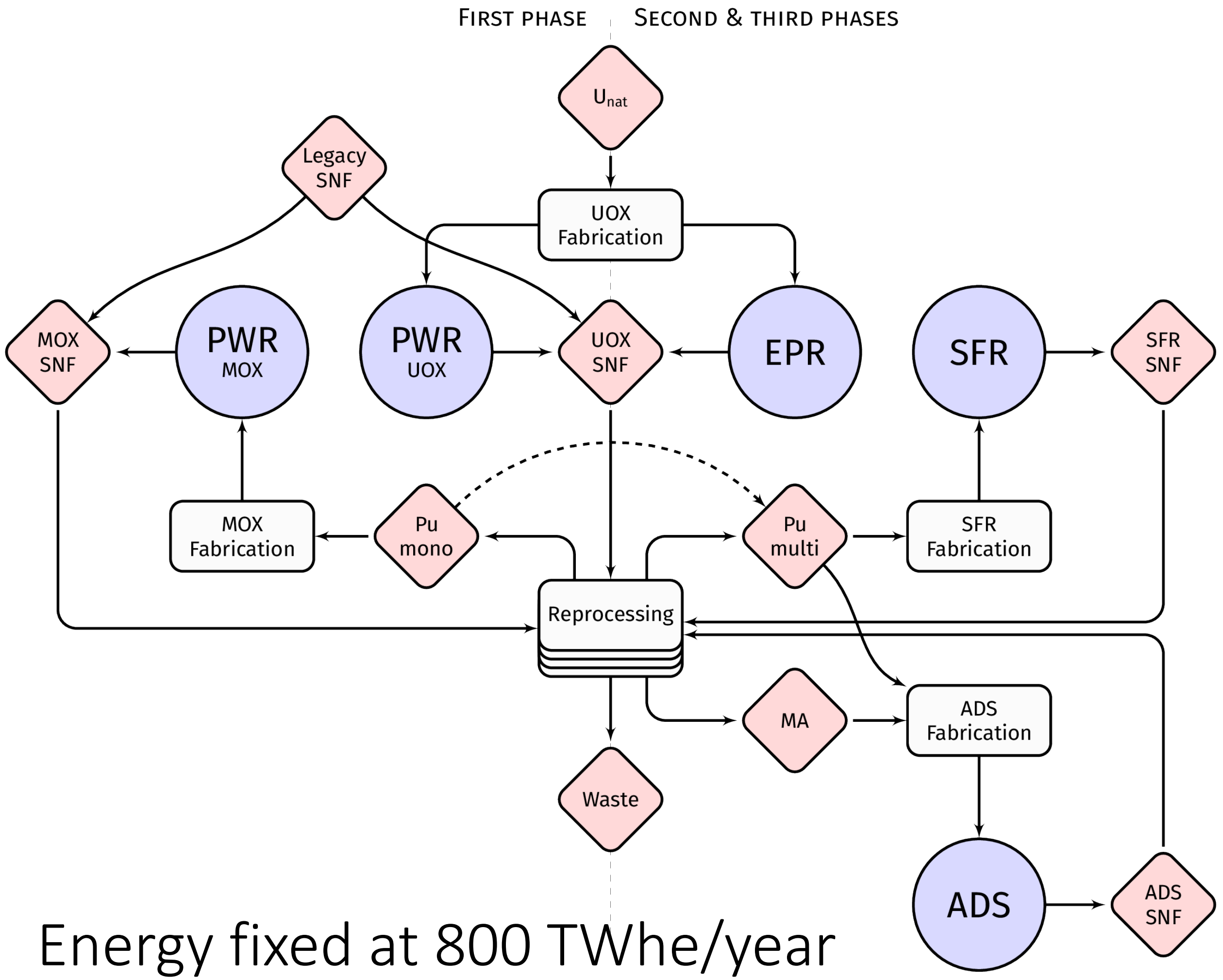

Transition scenario based on CP-ESFR project

- PWR(UOX+MOX)-> EPR + SFR + ADS
  1. Initial phase (2010 – 2040 years)
  2. Burning phase (2040 – 2100)
  3. Stabilization phase (2100 – 2300)
- SFR and ADS energies?
  - Minimize & Stabilize TRU
  - Minimize Cost (capital and O&M~80%)

Rodríguez, I. M., et al. "Analysis of advanced European nuclear fuel cycle scenarios including transmutation and economic estimates". In: *Annals of Nuclear Energy* 70 (Aug. 2014), pp. 240–247. 10.1016/j.anucene.2014.03.015.

$$\min_{x\in R^d}(m_{TRU}(\boldsymbol{x}), \mathrm{Cost}(\boldsymbol{x})) \text{ subject to } \begin{cases} \Delta m_{TRU}(\boldsymbol{x}) < 1t \\ m_{External}(\boldsymbol{x}) = 0 \end{cases}$$

(no additional mass)

Energy fixed at 800 TWhe/year

Reprocessing capacity 2000+800 t_{HM}/year (UOX + MOX)

Uncertainties ±10%

Results

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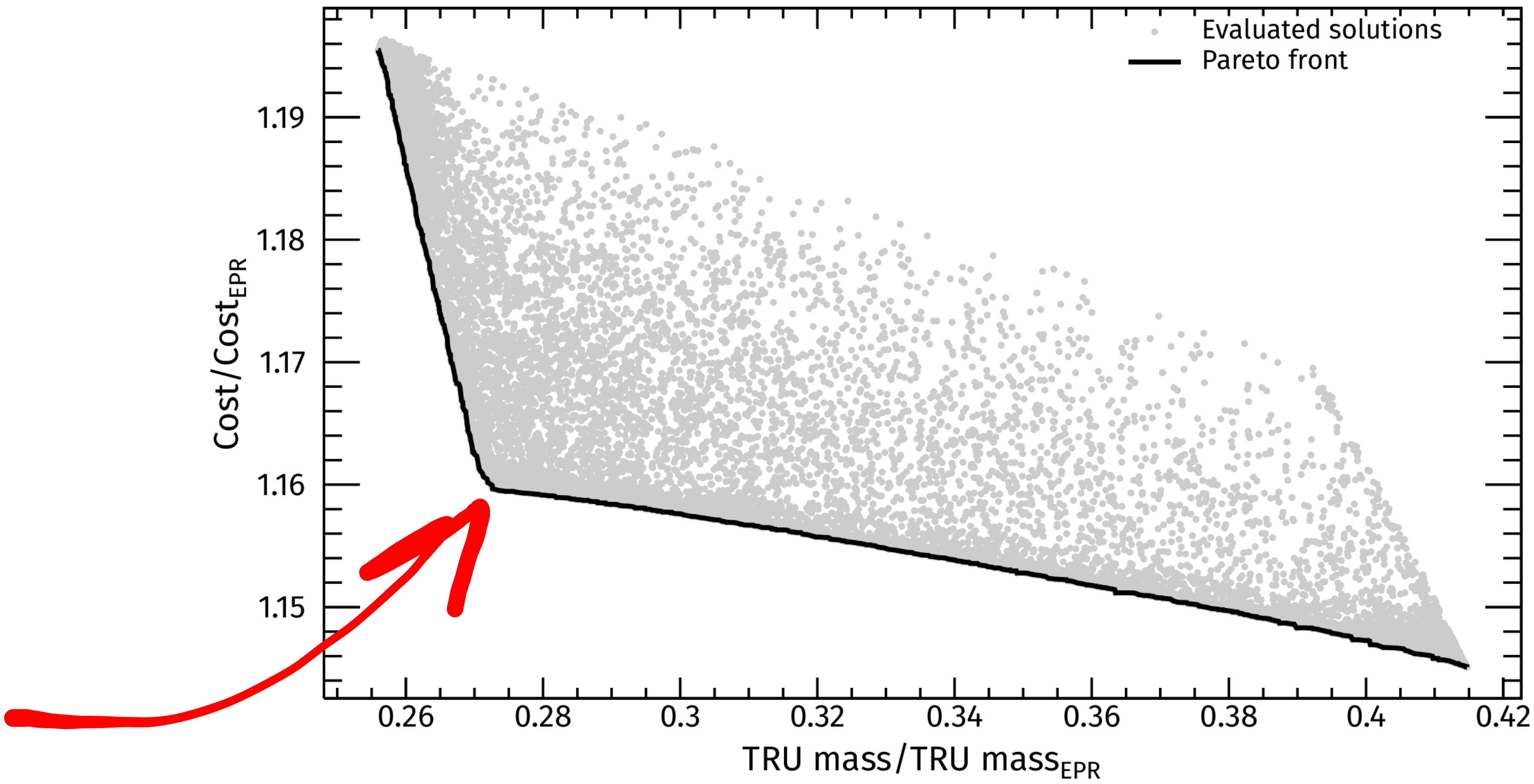
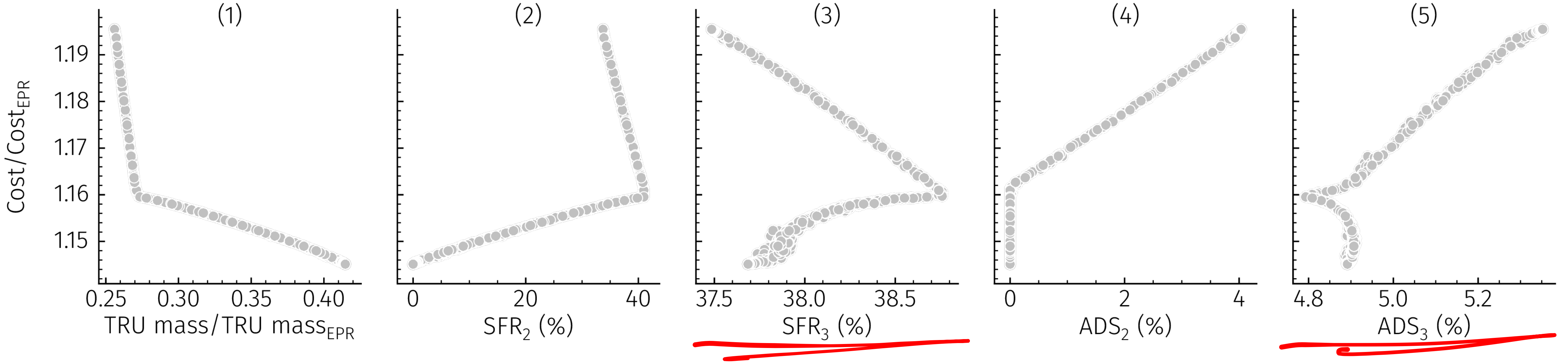
Solutions space: TRU reduction 60-75% with an overcost 15-20%



Results

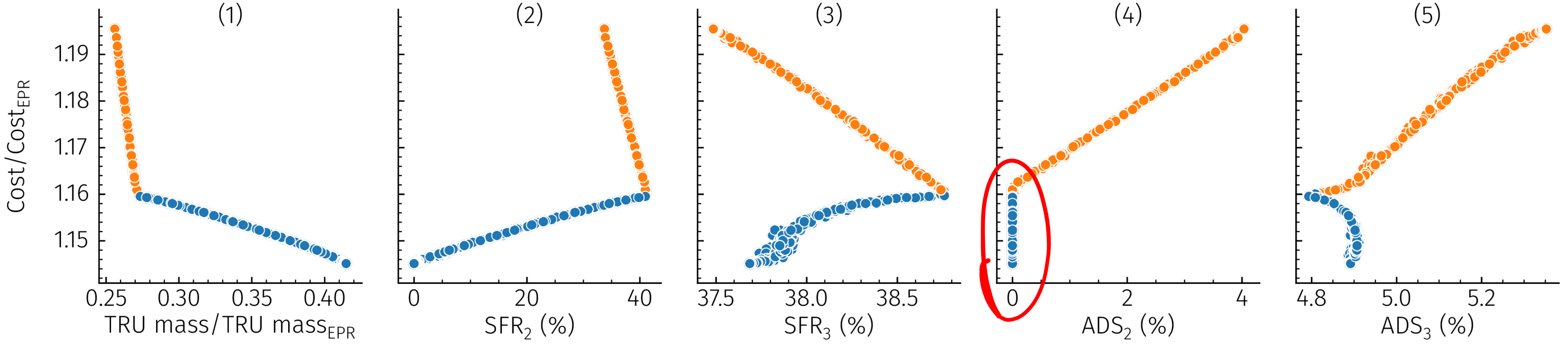
Input space



- The energy shares during the stabilization phase are quite insensitive to the burning phase
    - SFR ~ 37.5 – 38% (compared to 0-4%)
    - ADS ~ 4.8 – 5.3% (compared to 0-40% during burning phase)

Results

Input space



- The solutions are separable in two branches

Orange < 0.272 TRU mass/TRU mass$_{EPR}$ < Blue

- The introduction of ADS during the burning produces the cost increase

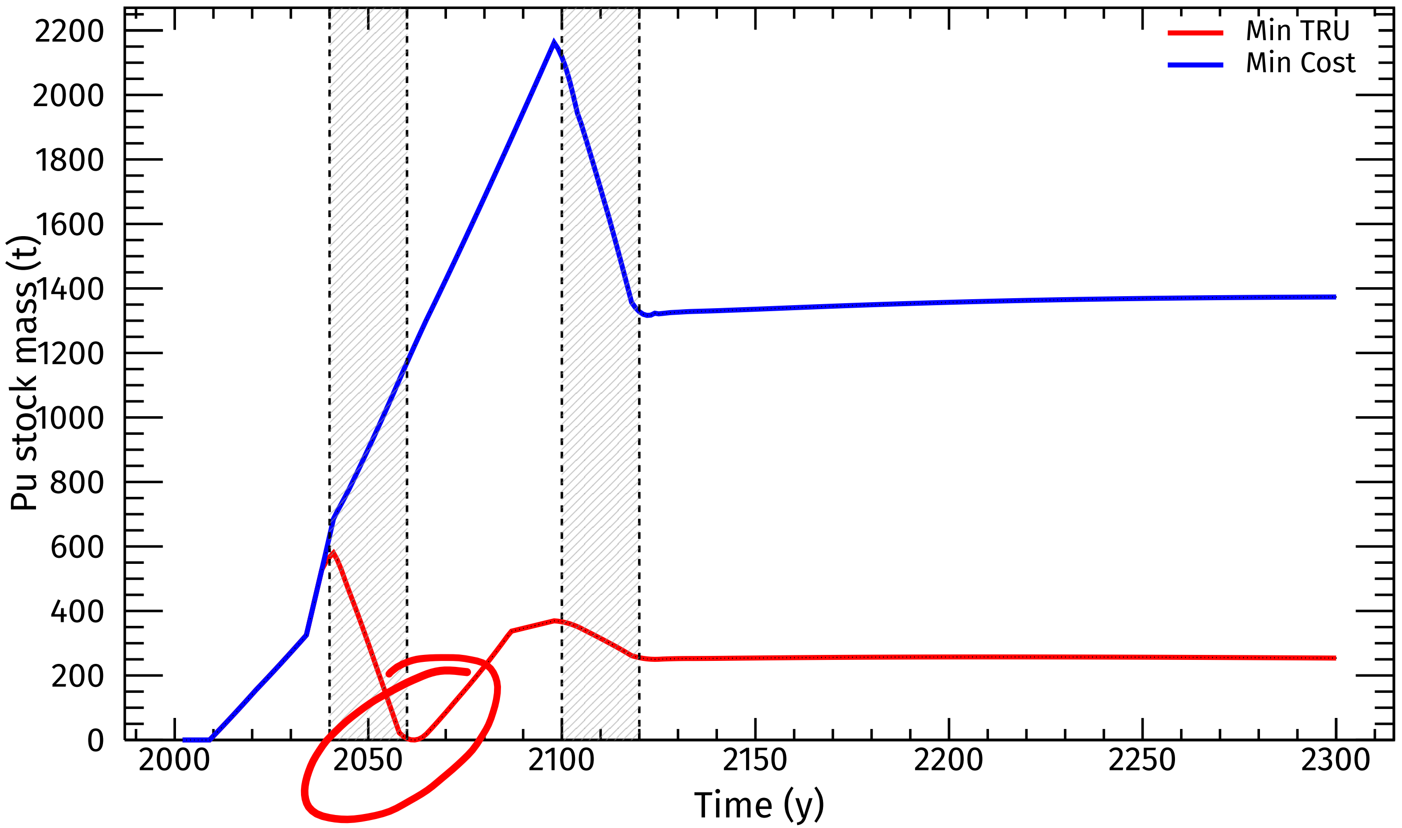
Uncertainties

The optimization pushes the scenarios to the limit

Small perturbations will produce a lack of material available for fabrication

- Disruption

Uncertainties can compromise the viability of the solutions



Uncertainties

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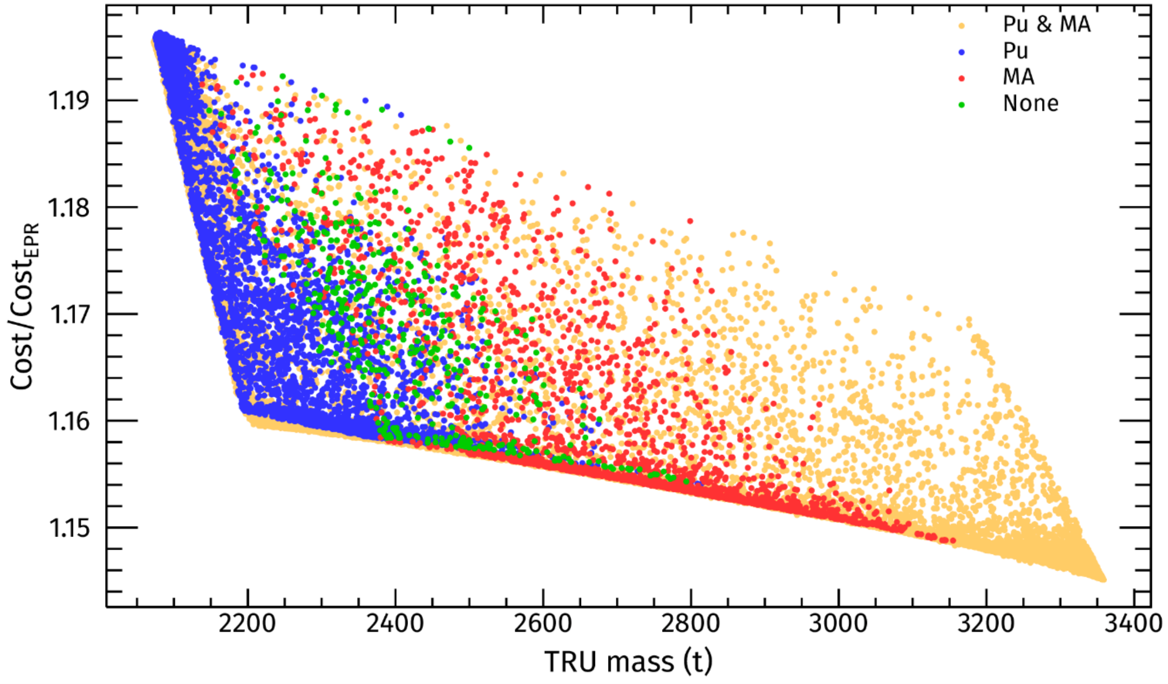
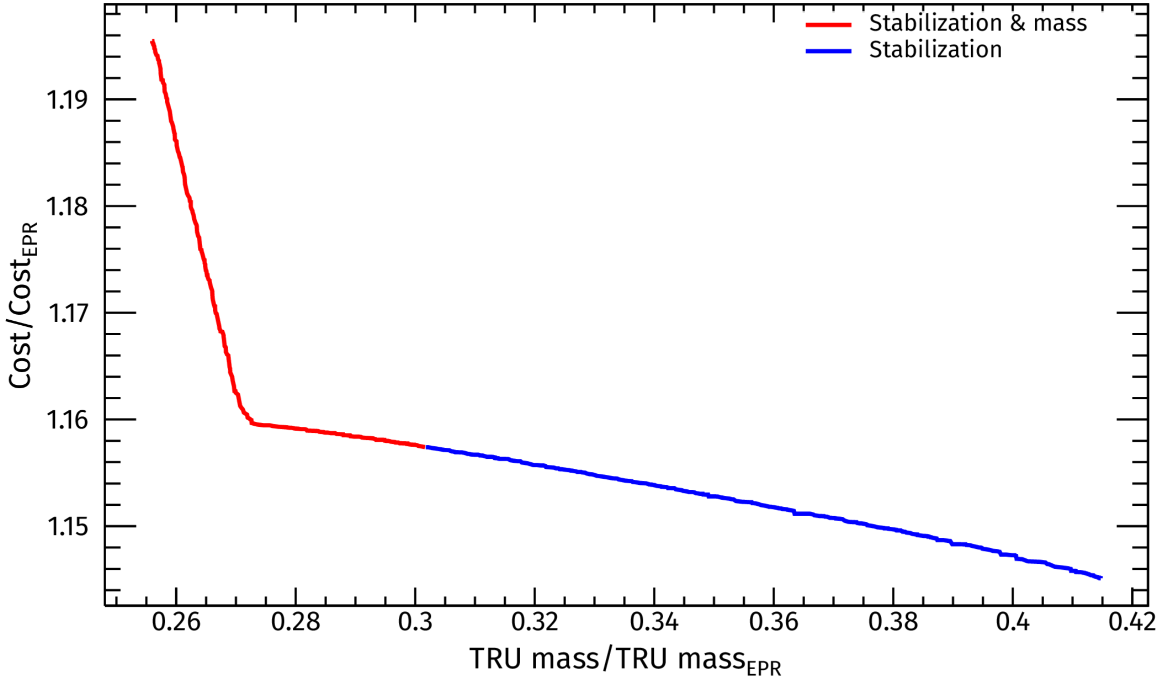
The introduction of the uncertainties (parametric variations) in the Pareto's front scenarios, shows that none of the solutions was robust

- All violates the stabilization constraint
- And a small subset requires an external mass

(those achieving the lower TRU)





Uncertainties should be taken into account during the optimization process!

Uncertainties

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In the presence of uncertainties, the evaluation of a set of input parameters does not produce a single value but a stochastic function

$$\min_{\boldsymbol{x}\in\chi} f(\boldsymbol{x}) \Rightarrow \min_{\boldsymbol{x}\in\chi} f(\boldsymbol{x},\boldsymbol{\xi})$$

By taking the expected value, it is possible to transform the problem into a deterministic one, and it can be estimated with the Sample Average Approximation (SAA)

$$E[f(\boldsymbol{x},\boldsymbol{\xi})] \approx \frac{1}{n}\sum_{i} f(\boldsymbol{x},\boldsymbol{\xi}^{(i)})$$

In order to reduce the computational cost, we will only perform parametric variations on the park energy and the reprocessing capacity

Uncertainties

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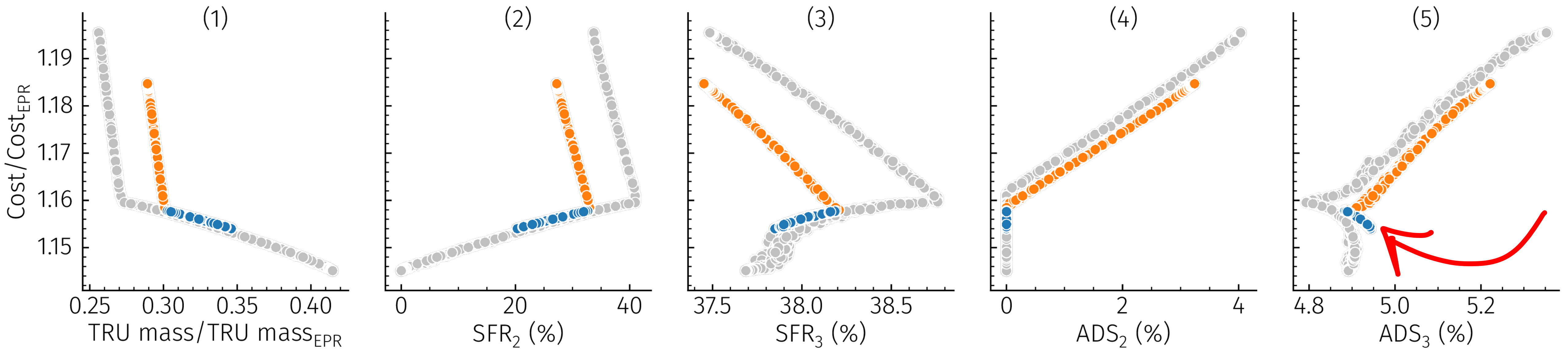
Input space



Orange < 0.301 TRU mass/TRU mass$_{EPR}$ < Blue

Uncertainties constraint the decision space (TRU reduction 65-71% with an overcost 16-18.5%)

Blue solutions except for ADS energy in stabilization phase almost coincide with reference case -> possibility of readaptation of the solutions?

Conclusions

- Optimization is an essential problem in fuel cycle studies for scenario planning
- Uncertainties play a decisive role in the validity of the solutions
  - The decision space can be highly affected as a consequence of the lack of robustness
  - And for extreme cases, no feasible solution may exist
- DEMO evolutive algorithm can be easily extended to handle uncertainties
  - Although the computational cost can be prohibitively large

Question

How do you handle huge datasets for exploratory data analyses?