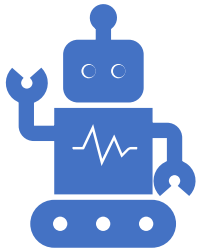
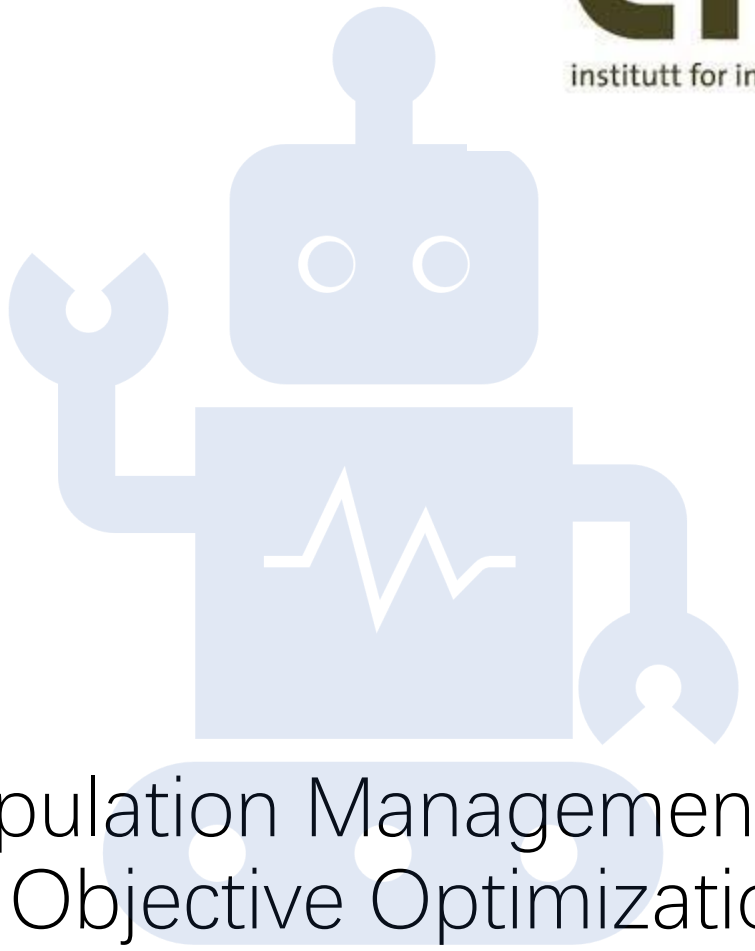


UiO : University of Oslo

institutt for informatikk



IN3050/IN4050 - Introduction to Artificial Intelligence and Machine Learning



Evolutionary Algorithms – Population Management, Hybrid Algorithms and Multi-Objective Optimization

Kai Olav Ellefsen

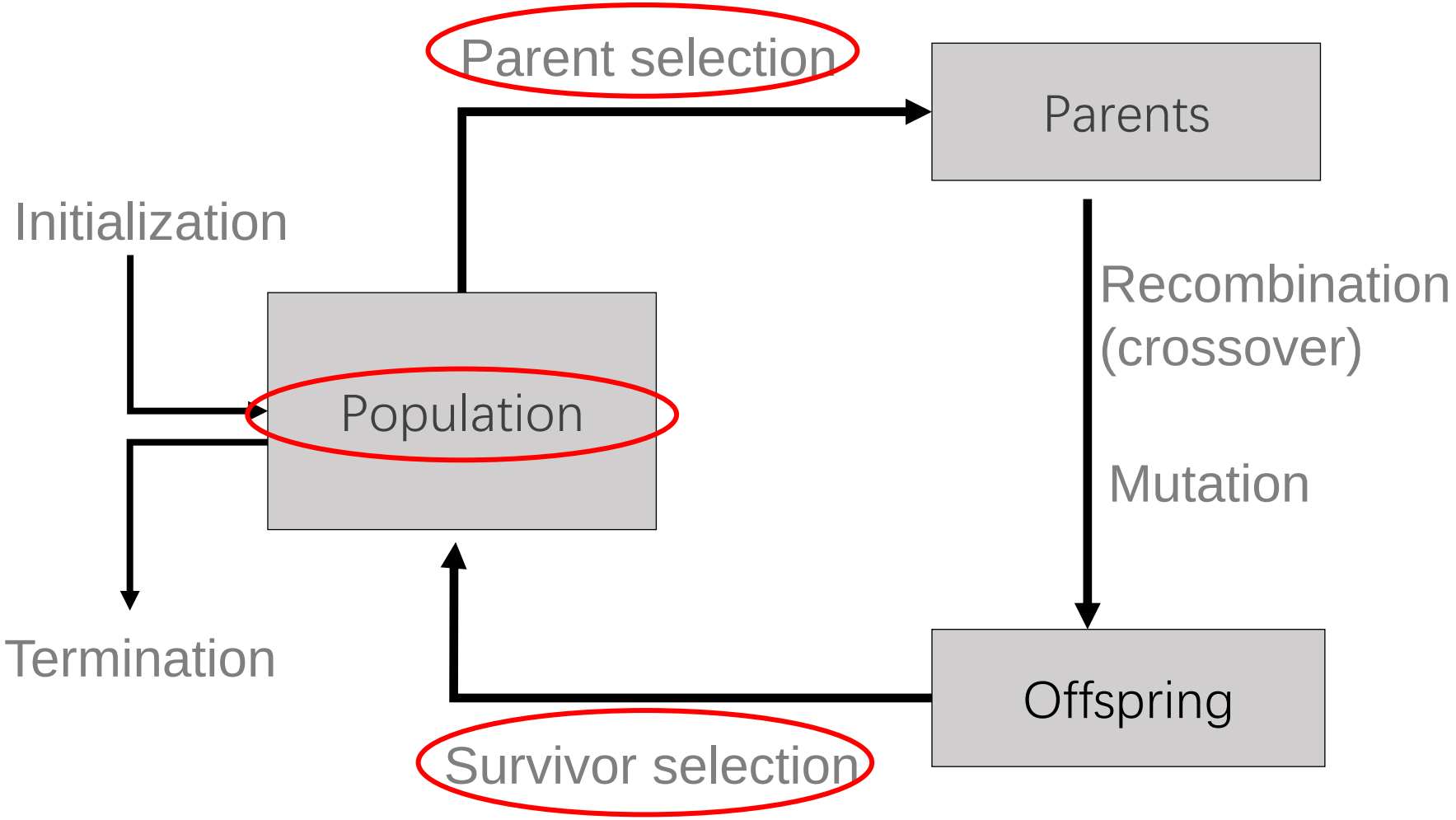
Today

- Evolutionary Algorithms part 2: Summary, demos, examples
  - Selection and preserving diversity
  - Hybridization
  - Multiobjective Evolutoionary Algorithms (MOEAs)
- Dialog/discussion
- Next week's topic: Supervised Learning

Practical Information

- First mandatory exercise online
  - Topic: Optimization techiques
  - Solving Travelling Salesperson problem with exhaustive search, hillclimbing and evolutionary algorithm
  - Deadline: 28. February

Evolutionary Algorithms – Part 2



Selection-Some key topics

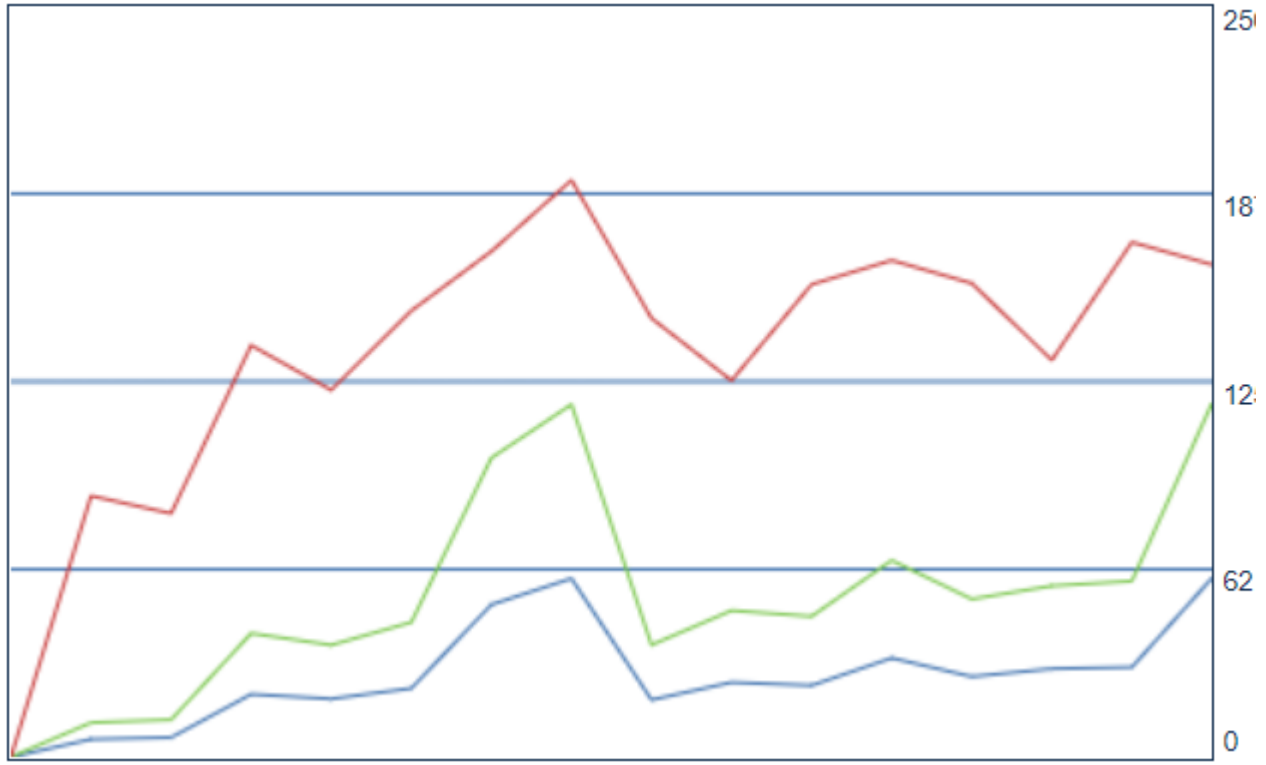
- Selection pressure
  - **Do you see a connection to the «Temperature» in Simulated Annealing?**
- Different types of selection
  - Fitness proportionate
  - Rank-based
  - Tournament
- Elitism

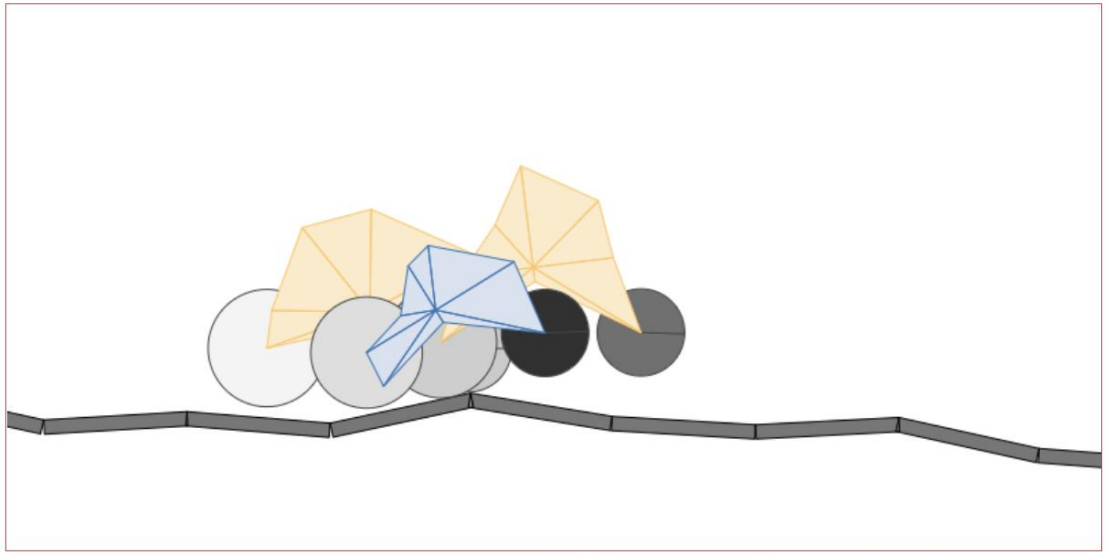




Tricky Quiz: https://rednuht.org/genetic_cars_2/

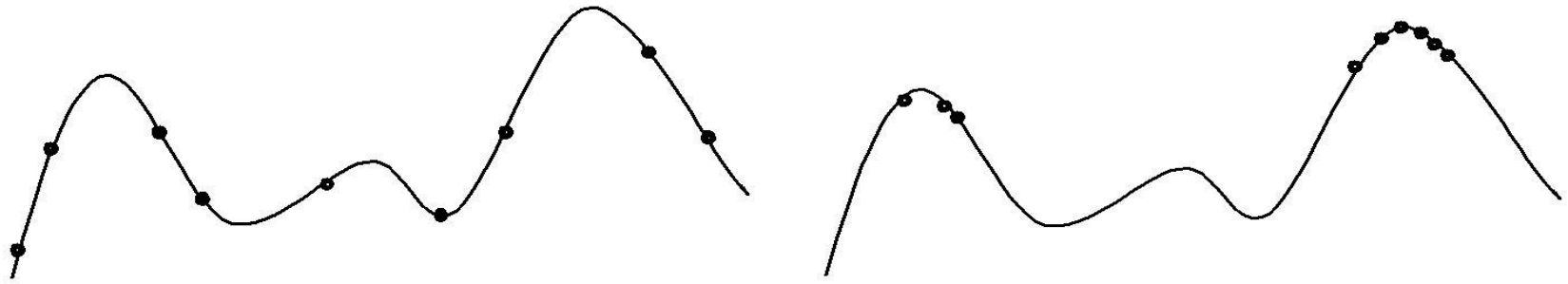
- These fitness graphs are from a run with **elitism**
- How can the graph still dip?





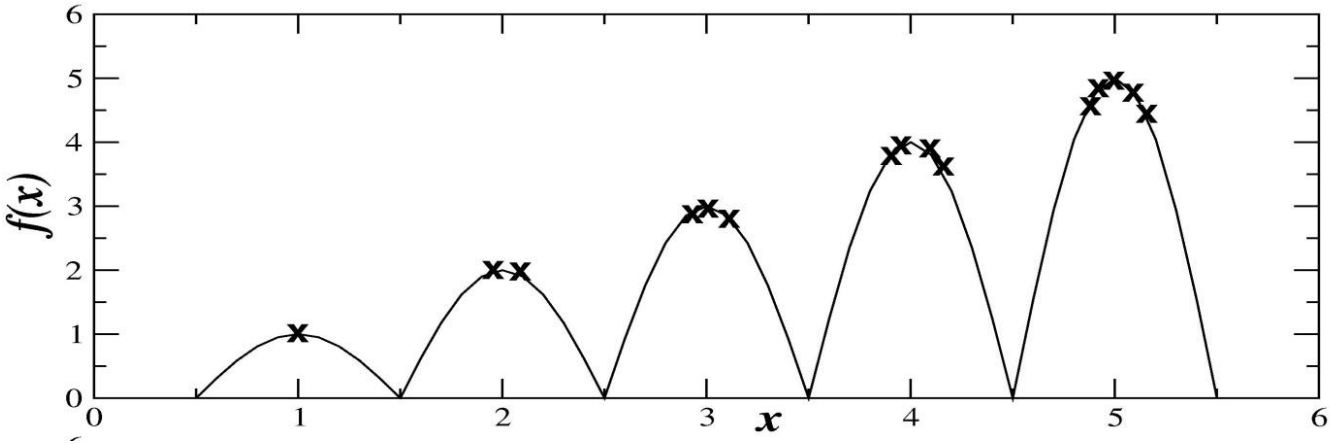
Multimodality

- Often might want to identify several possible peaks
- Different peaks may be different good ways to solve the problem.
- We therefore need methods to **preserve diversity** (instead of converging to one peak)



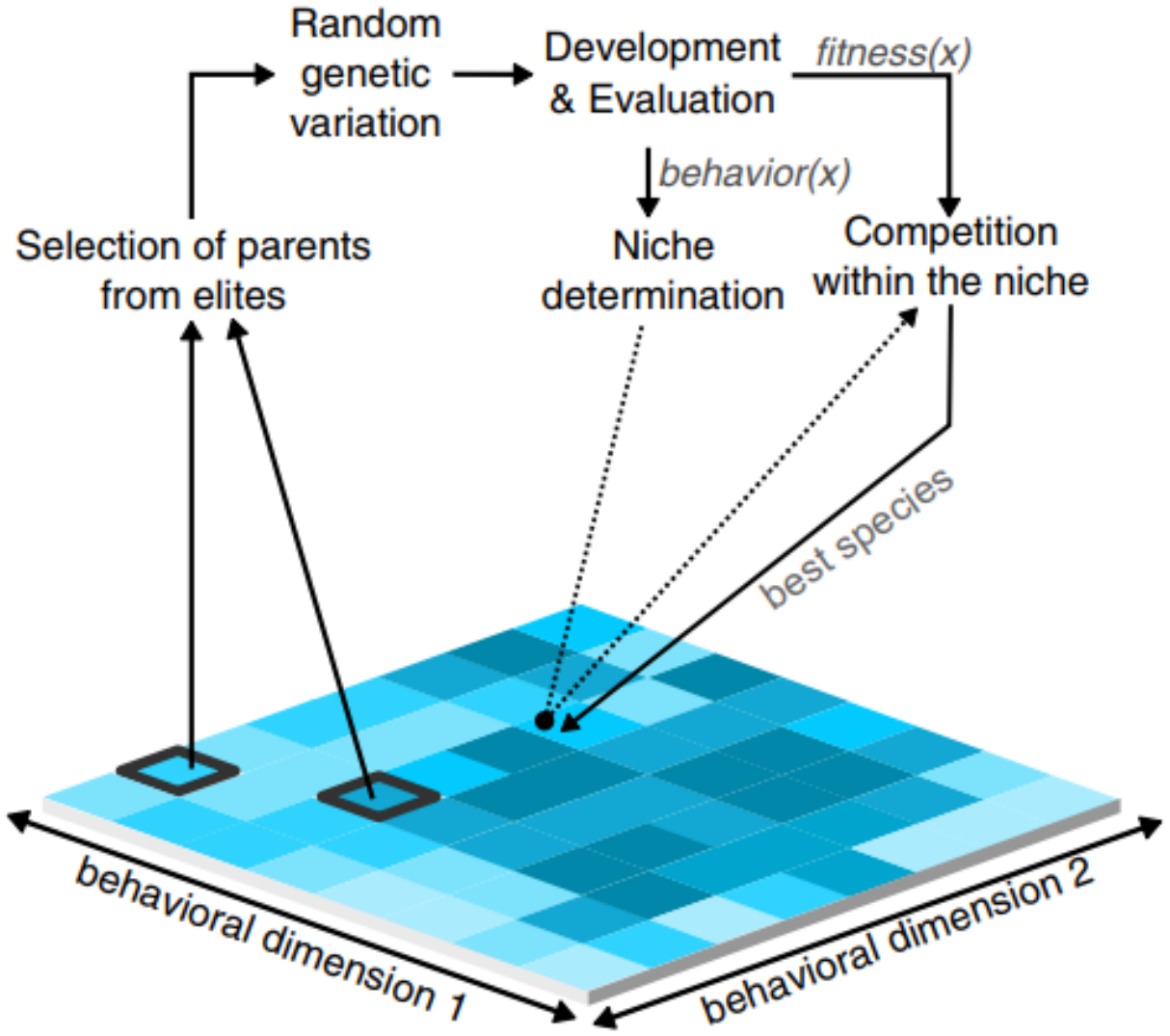
Diversity Preservation – Key points

- Identifying multiple peaks in fitness landscape can be beneficial
- Approaches for preserving diversity:
  - Island models
  - Speciation
  - Fitness sharing
  - Crowding



Modern Diversity Preservation: Quality-Diversity Algorithms

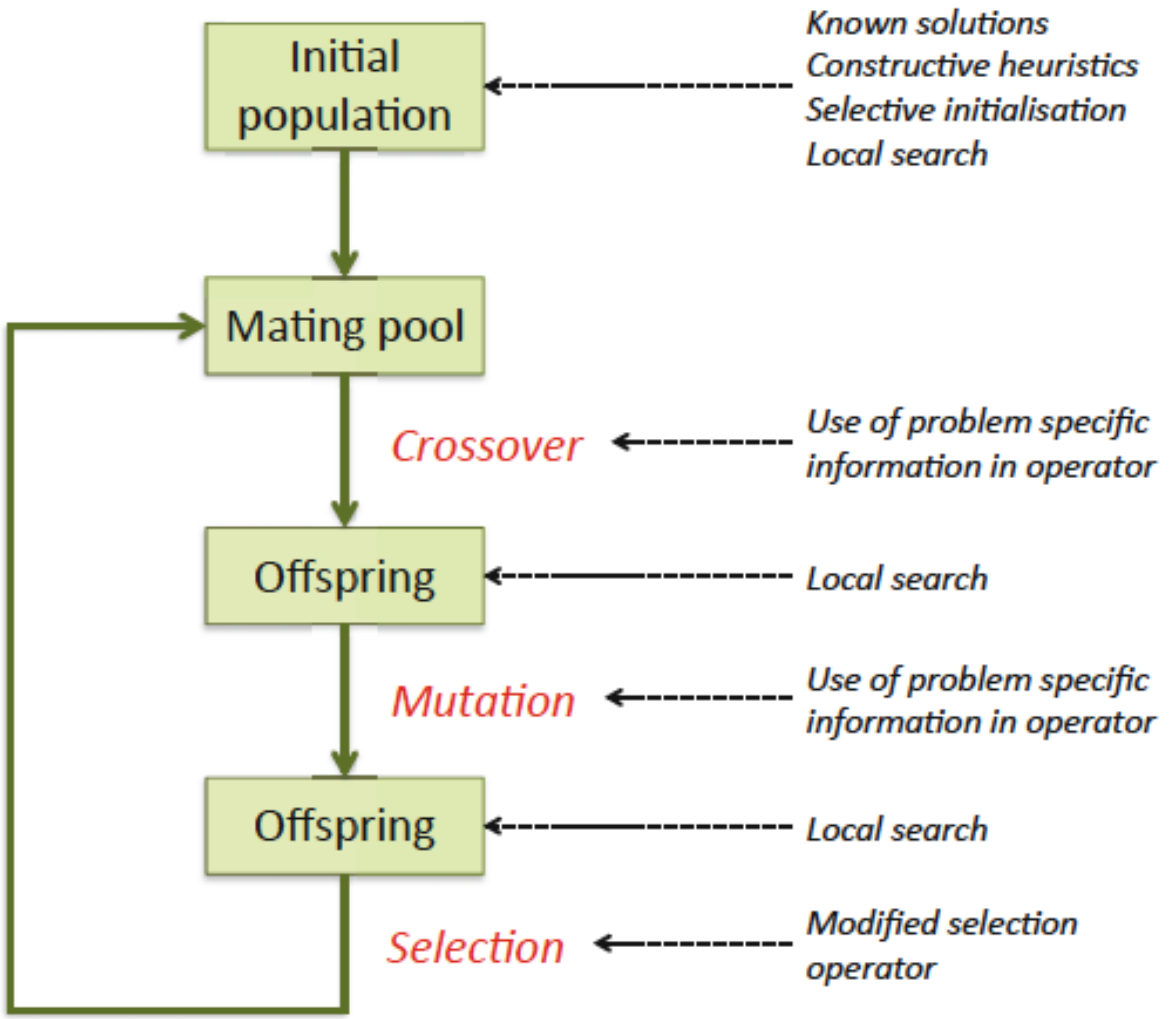
- Explore a «map» where each square has a different variation of your goal (ensures *diversity*)
- Inside each square: Elitism (ensures *quality*)
- The *whole map is filled in one run*, giving an efficient search

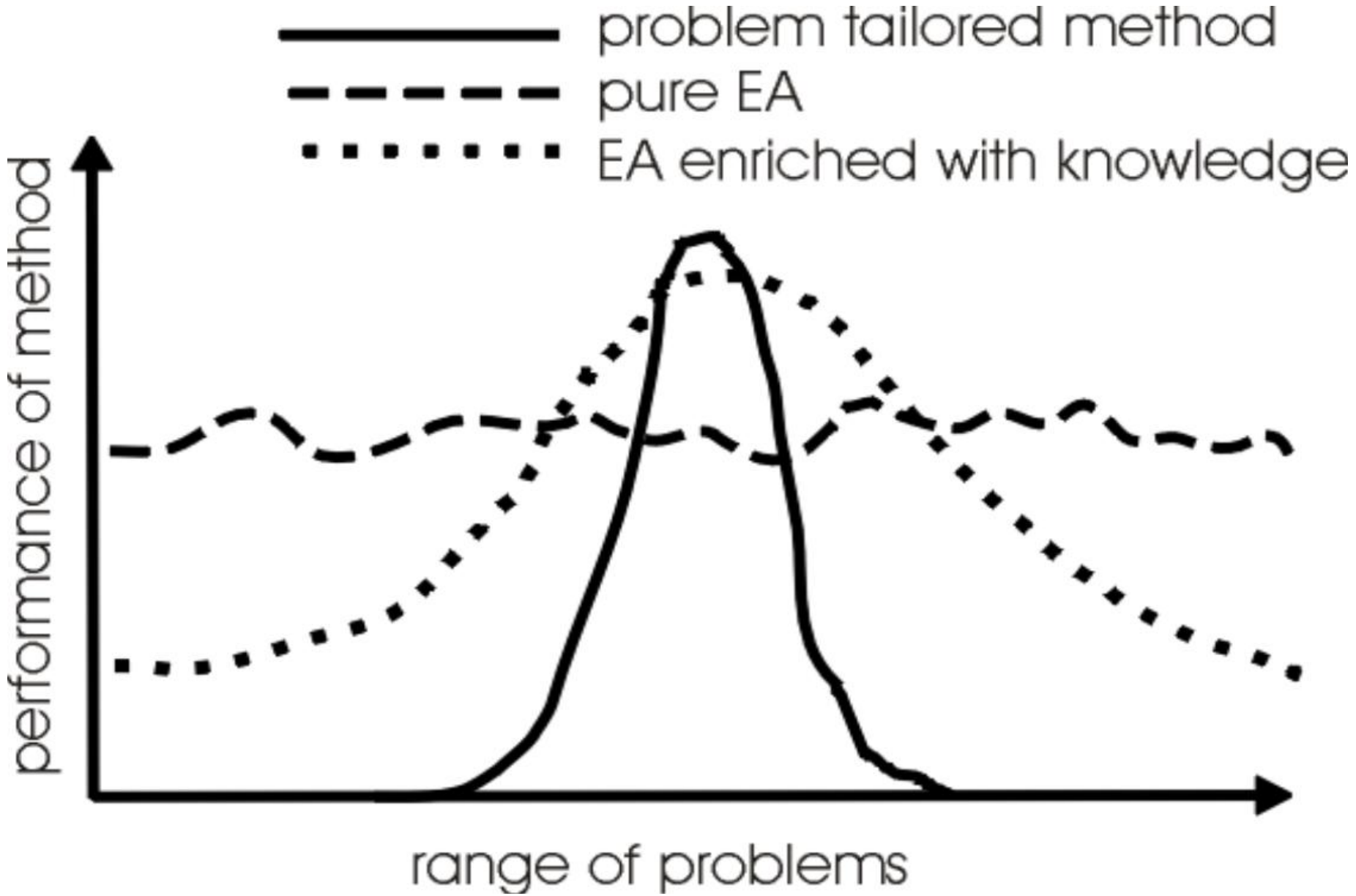


Jean-Baptiste Mouret. Evolving the behavior of machines: from micro to macroevolution. iScience, Elsevier, 2020,

Hybridization – Key points

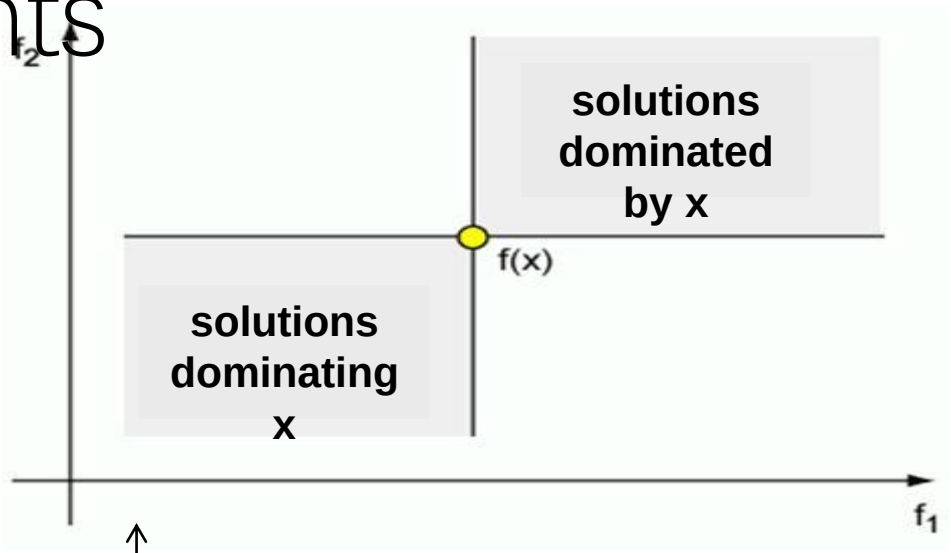
- Very common for practical applications of Eas
- Often we have **problem-specific knowledge** that we can use to **reduce the randomness** in the search.
- Or we can combine the EA with local searches

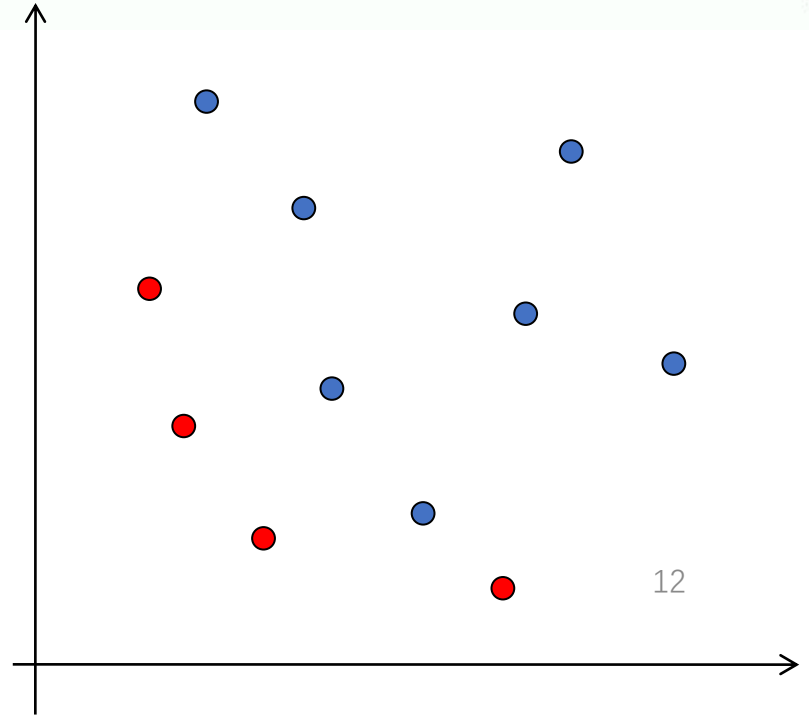


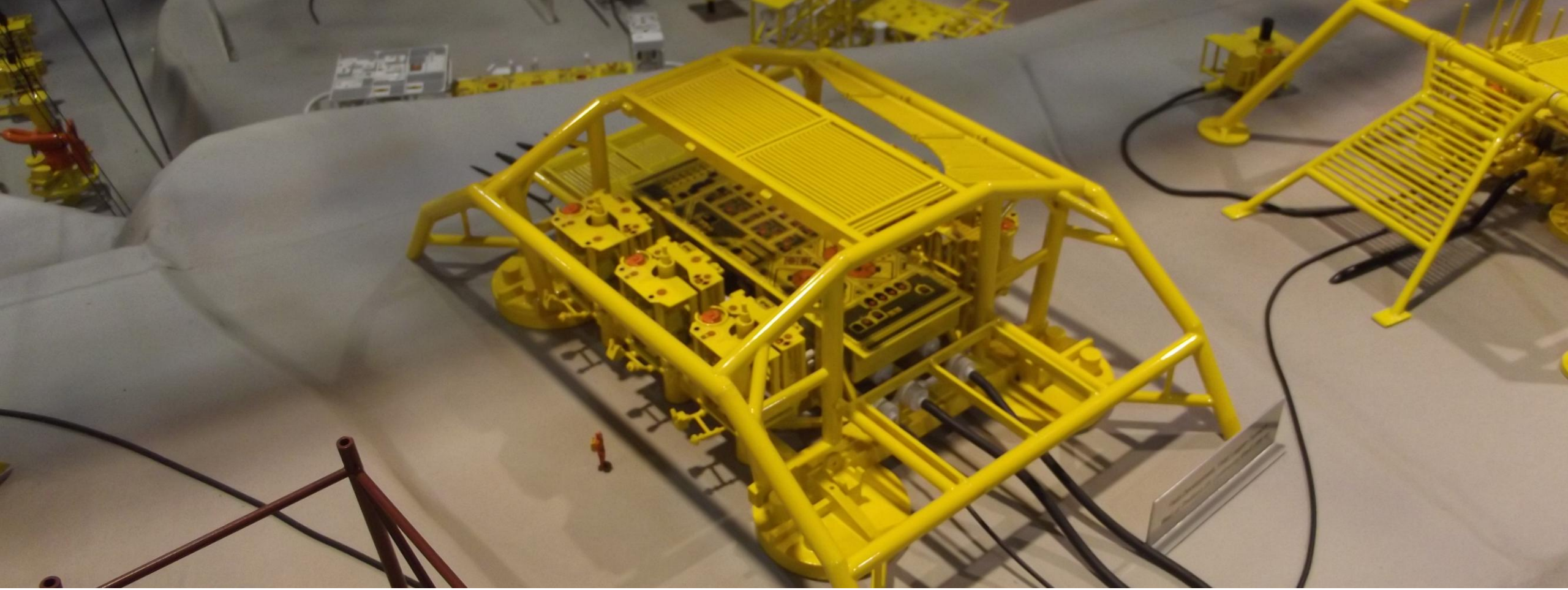

problem tailored method
pure EA
EA enriched with knowledge
performance of method
range of problems

Multiobjective EAs – Key points

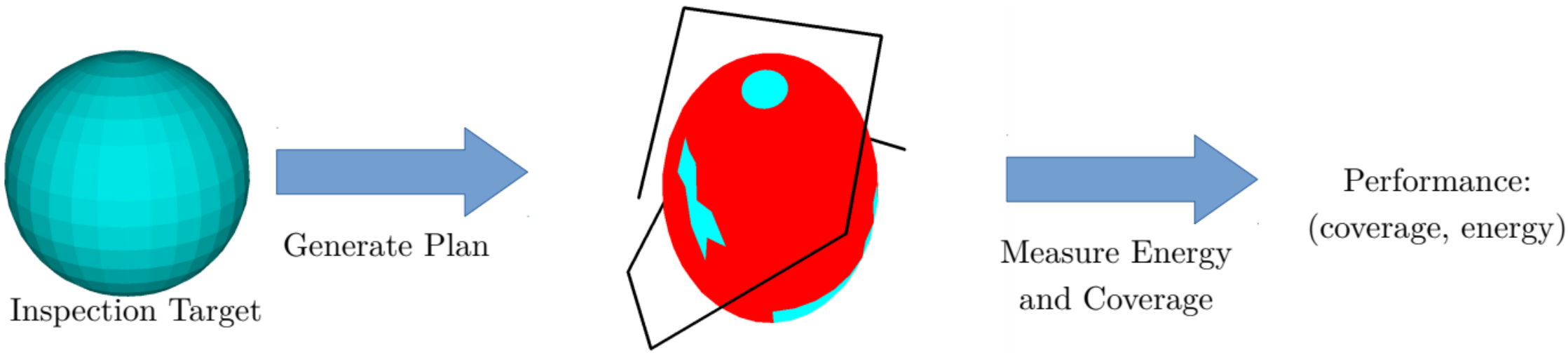
- Many practical problems have conflicting objectives
- Dominance in multiobjective problems
- The Pareto Front
- Goal of MOEAs: Approximate the pareto front, and be well distributed along it
- Special techniques for selection, diversity preservation and archiving





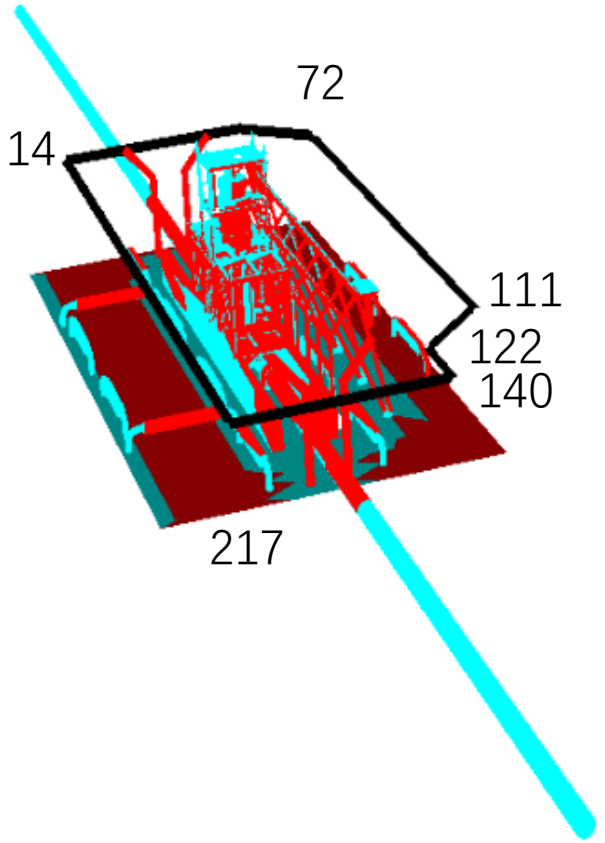


Multiobjective EA Example

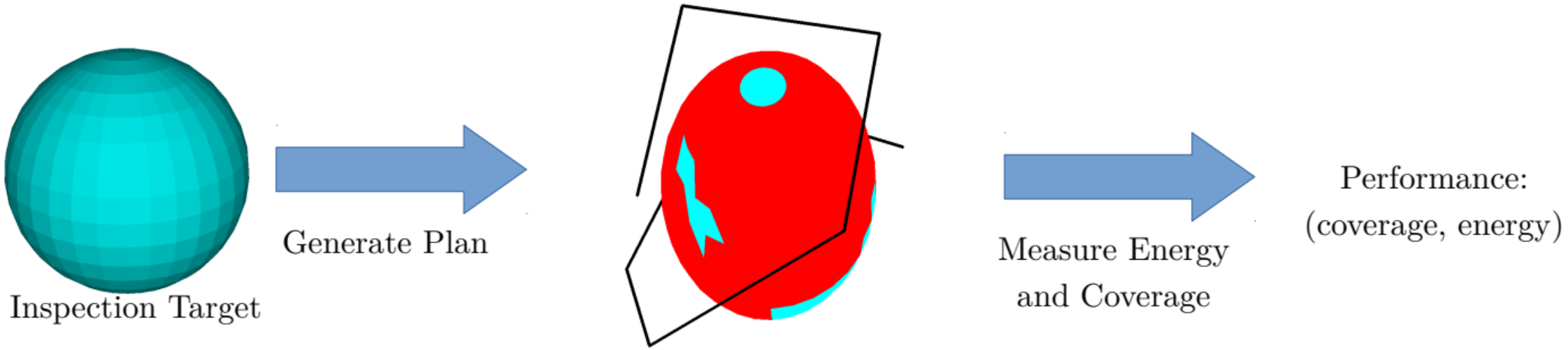

Inspection Target
Generate Plan
Measure Energy
and Coverage
Performance:
(coverage, energy)

Last week: How to represent plans

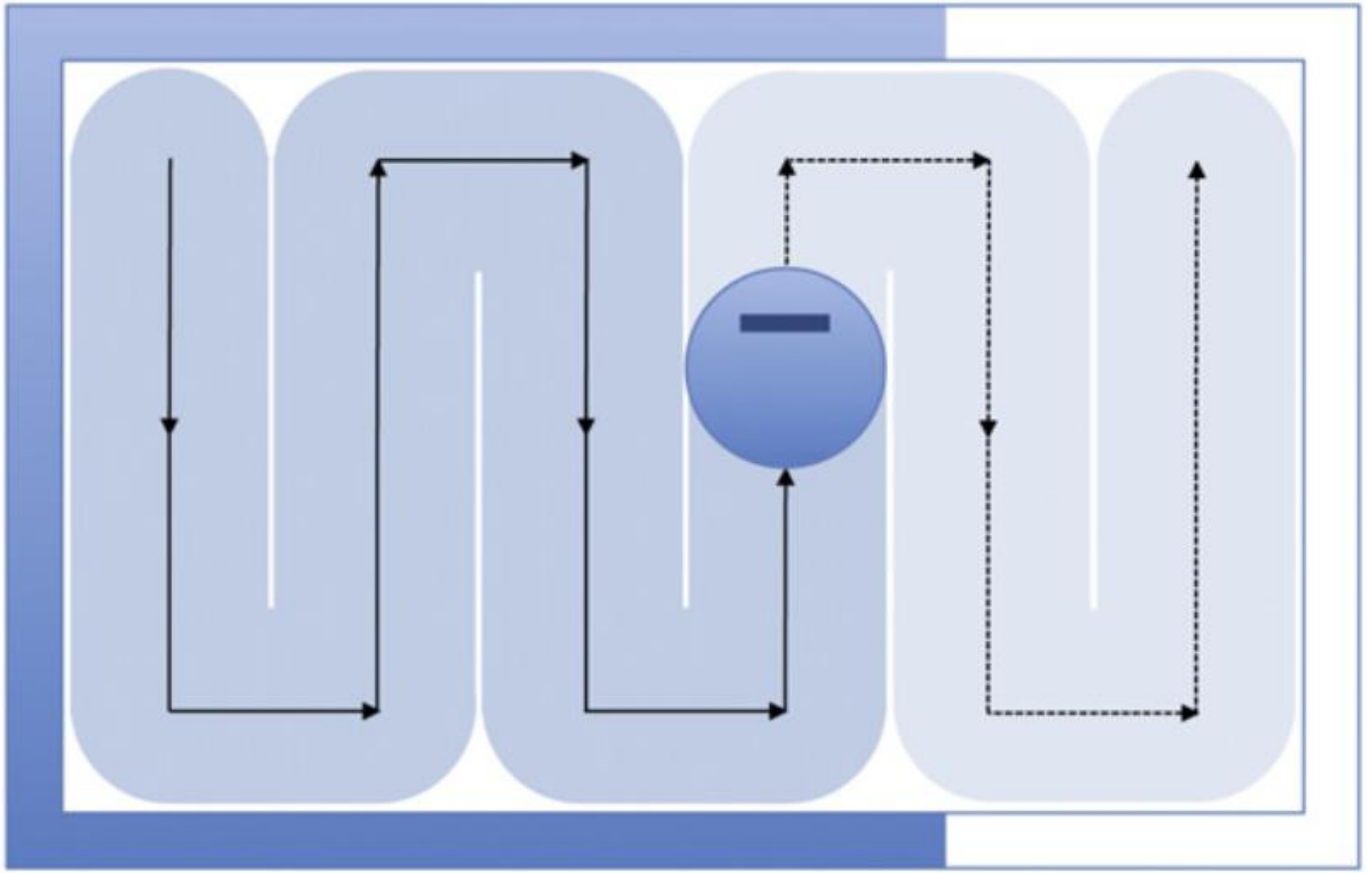
- The EA has to be able to:
  - Make small changes to the plan (*mutation*)
  - Combine plans (crossover)
  - Evaluate the plan (calculate its *length*)
- Given some inspection target:
  - How do we represent a path moving around that target in a way the EA can “understand”?



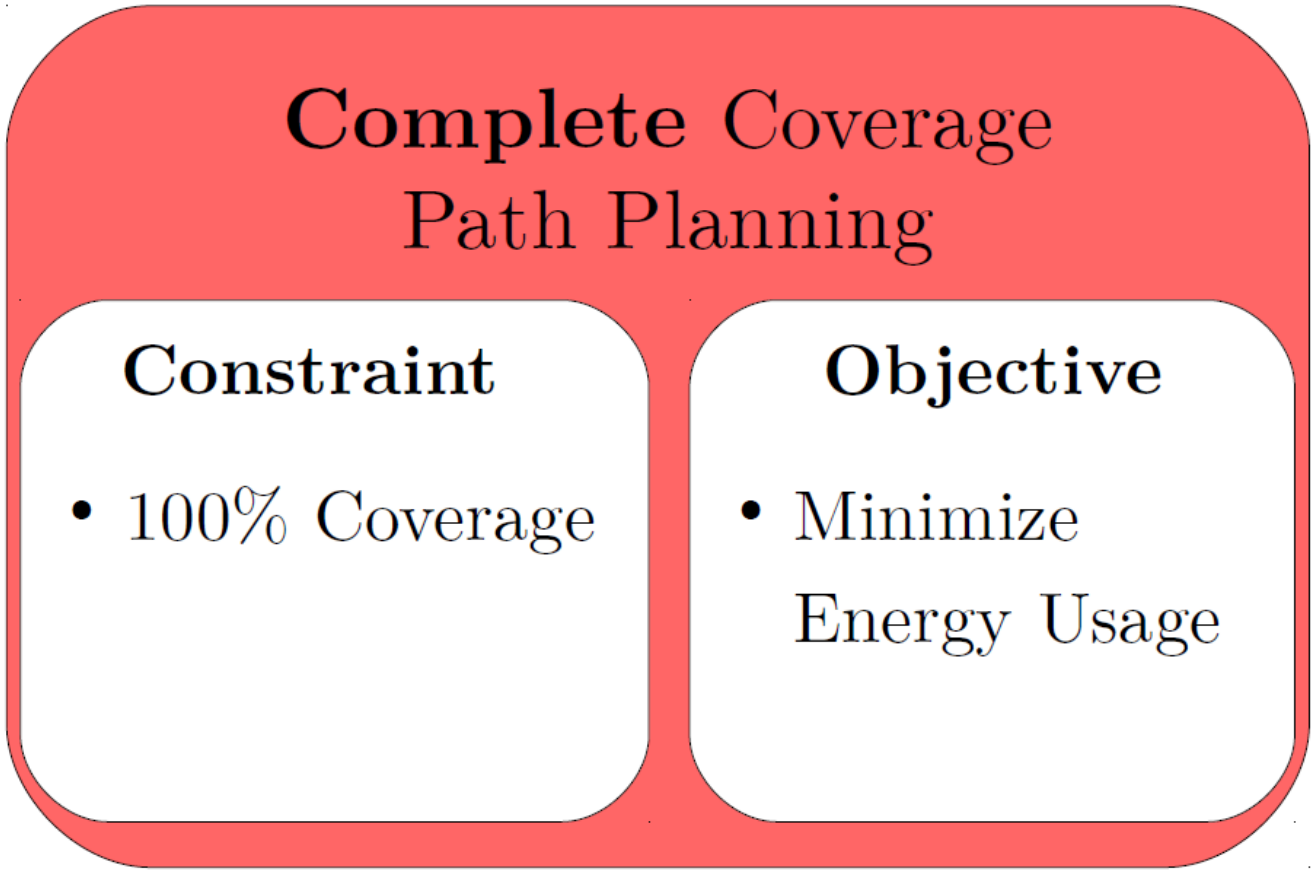
This week: Multiple objectives, and hybridization



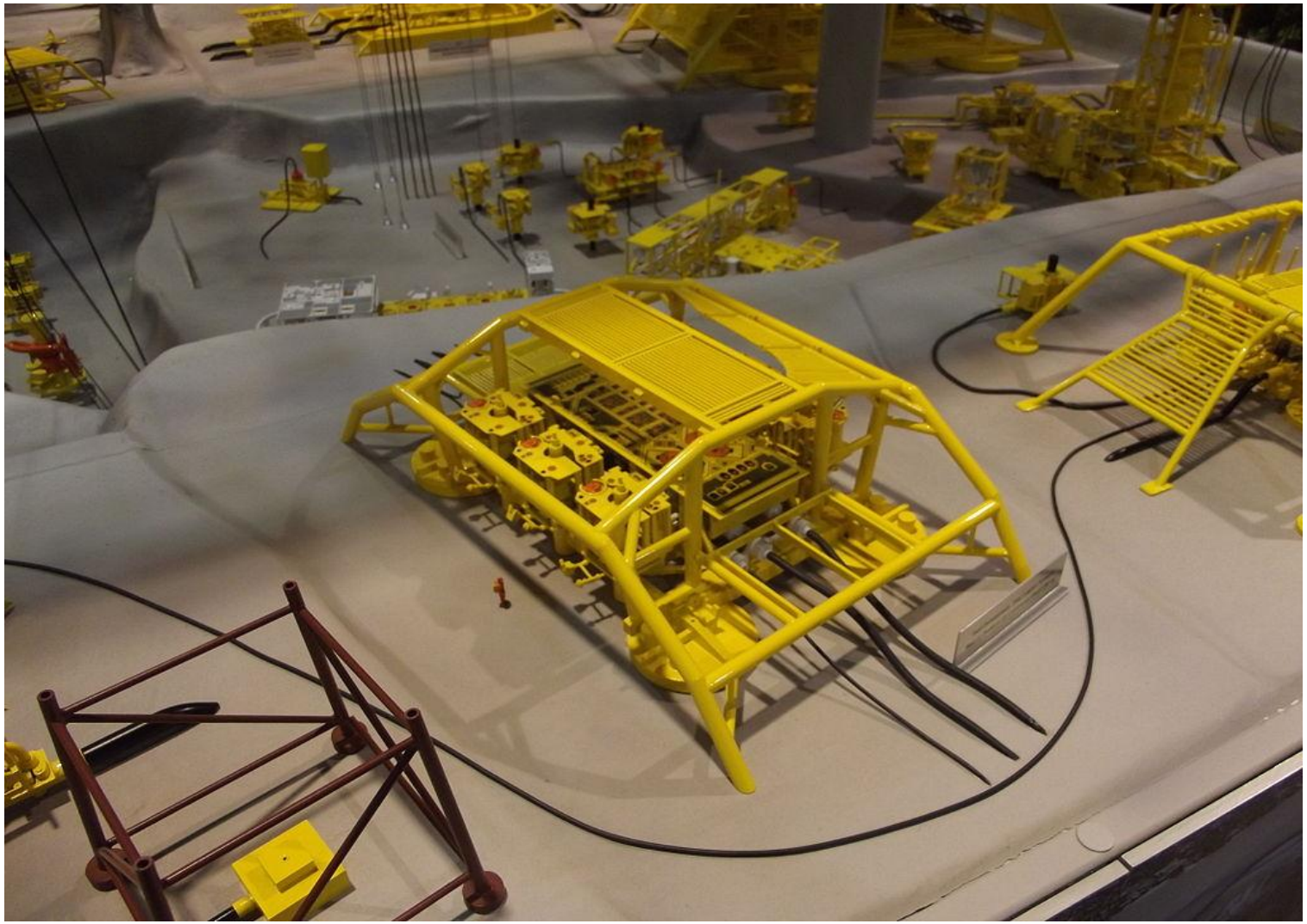
Coverage Path Planning



Limitation of Previous Methods



Complete Coverage May Be Impossible



Complete Coverage Path Planning

Constraint

- 100% Coverage

[redacted]

Objective

- Minimize Energy Usage

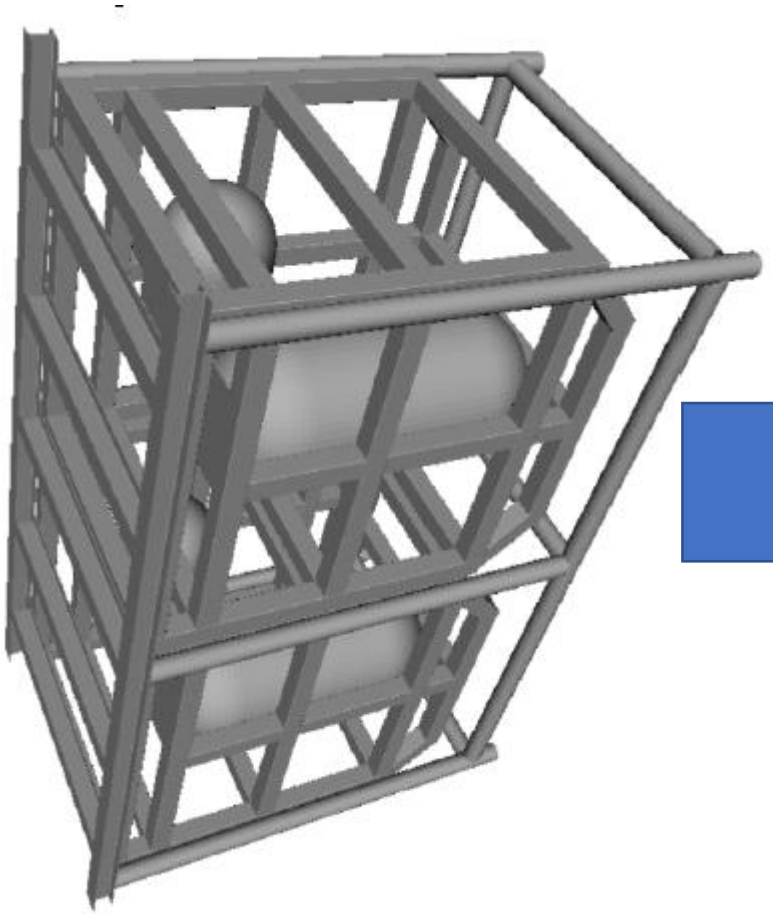
Multiobjective Coverage Path Planning

Objectives

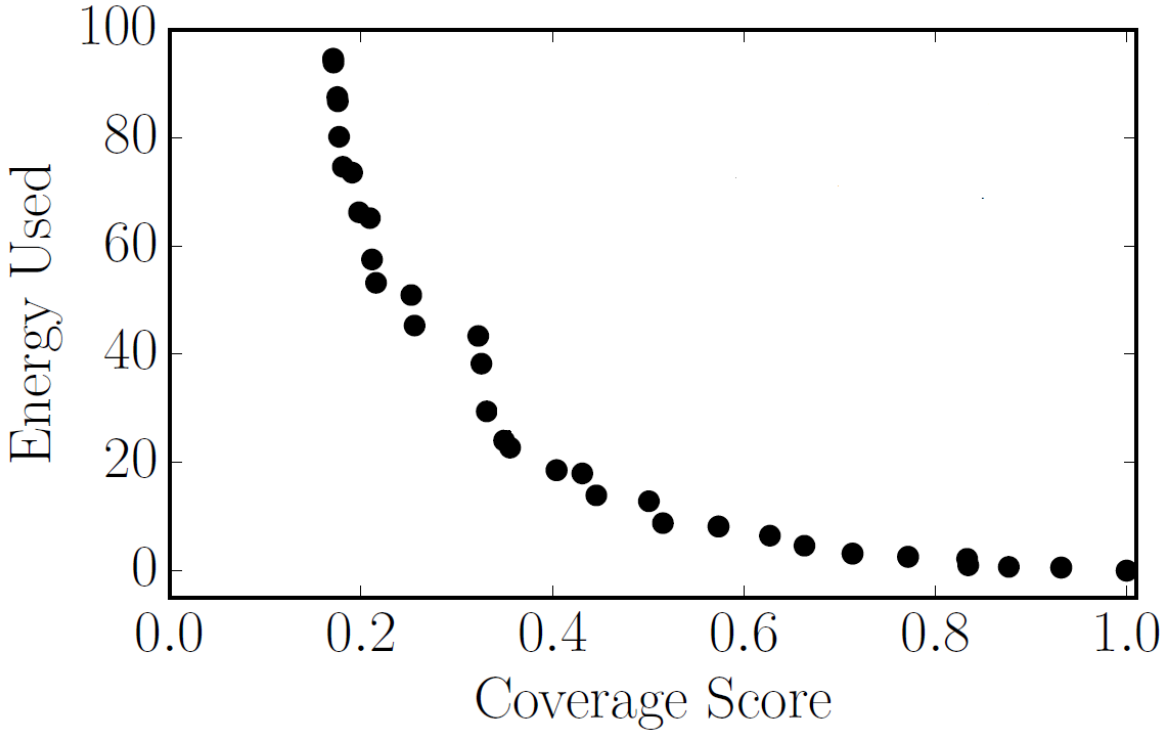
- Minimize Energy Usage
- Maximize Coverage

[redacted]

Proposed Solution

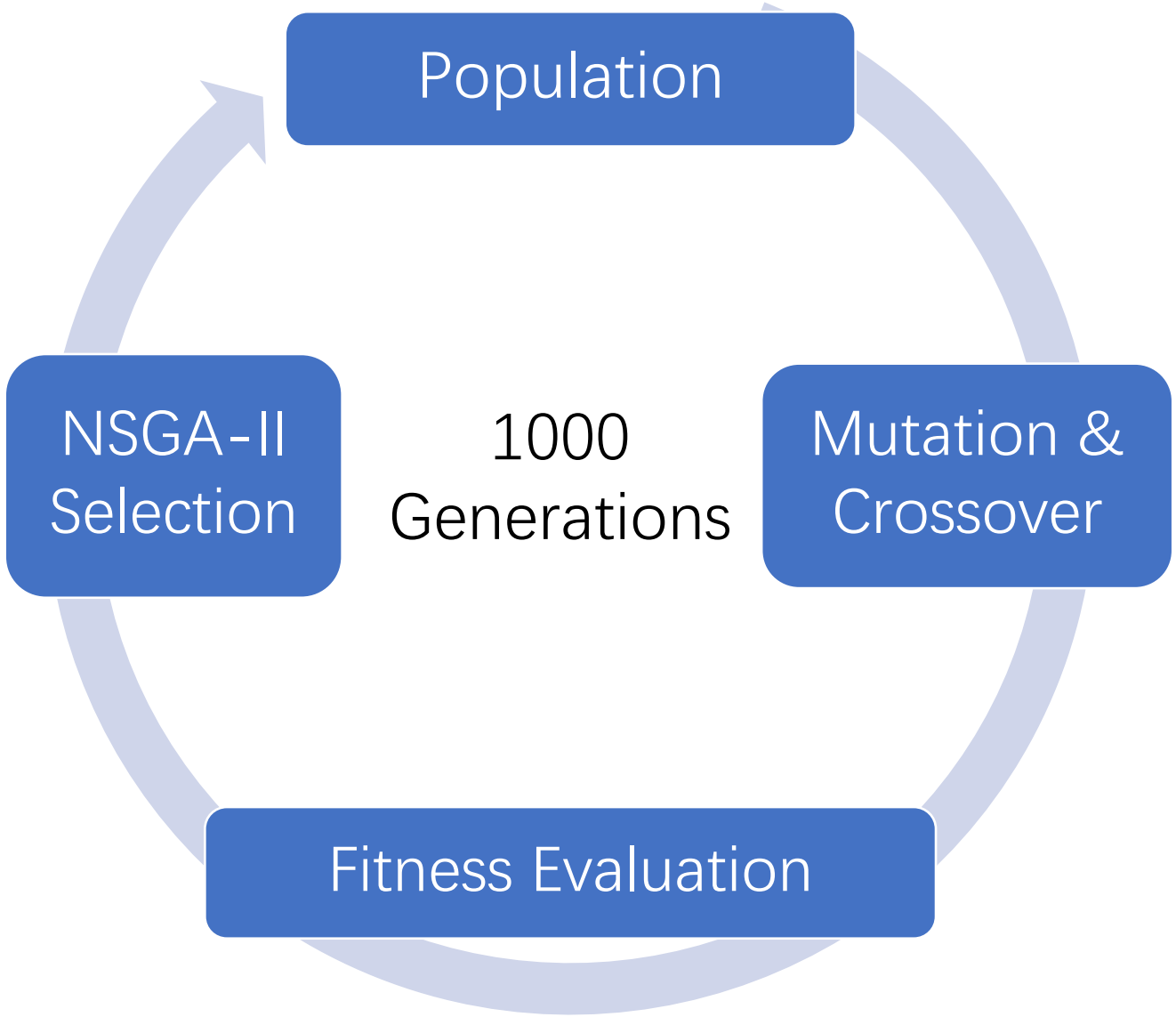


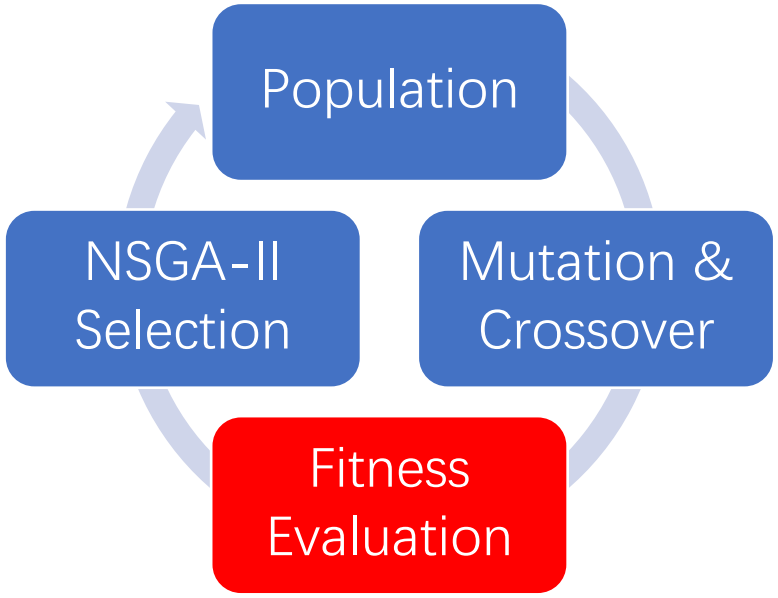
NSGA-II



Input: 3D Model

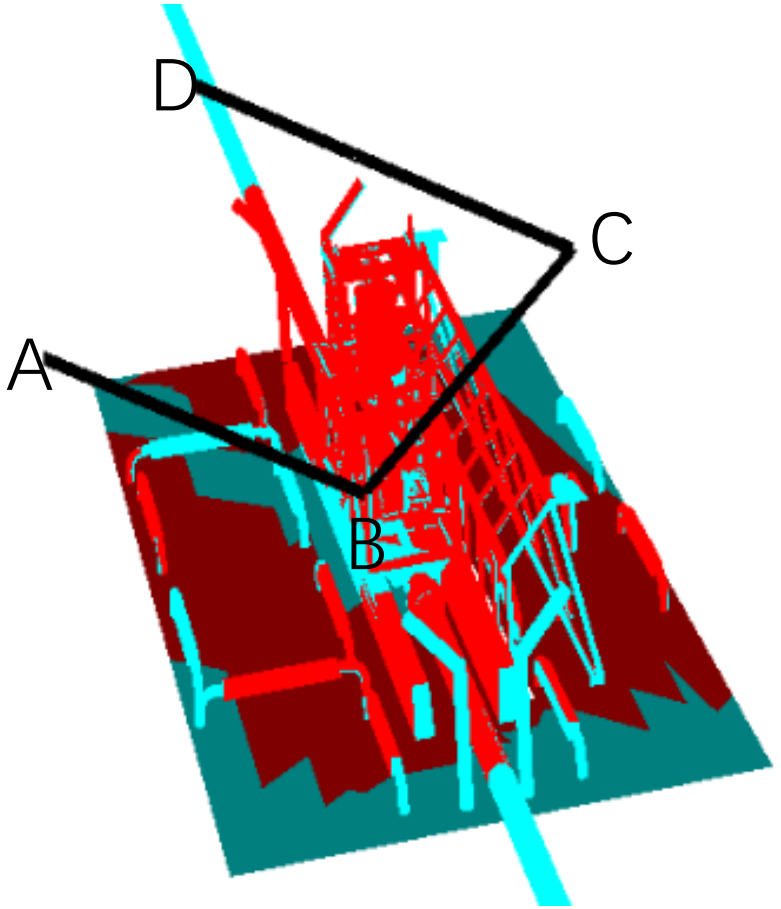
Output: A population of plans

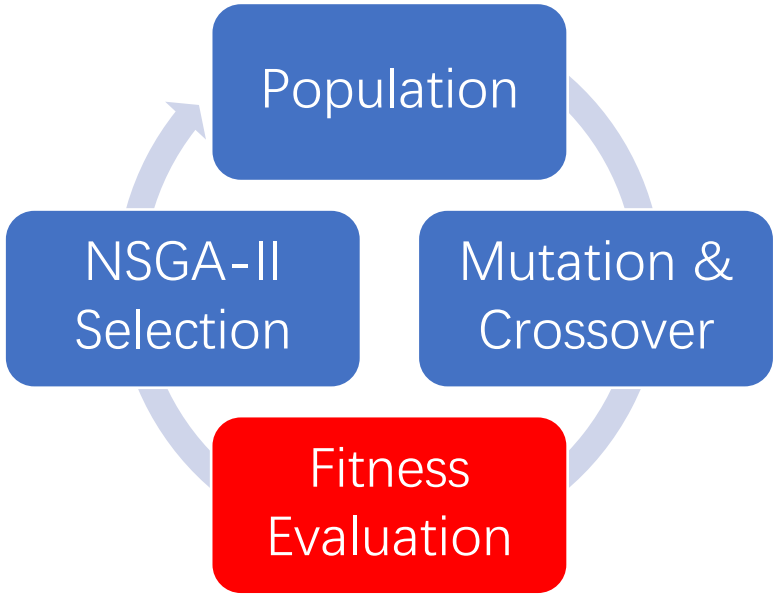

Population
Mutation & Crossover
Fitness Evaluation
NSGA-II Selection
1000 Generations



1. Decode genotype into plan

[A, B, C, D] ->

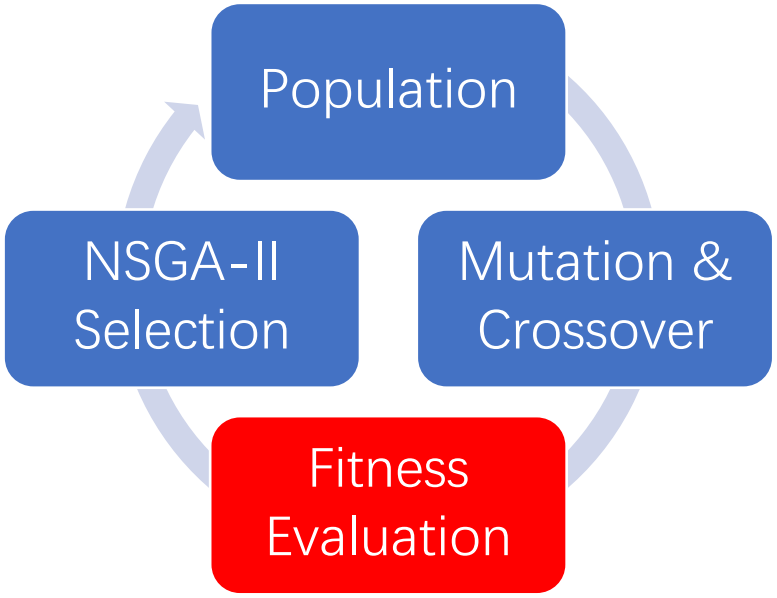


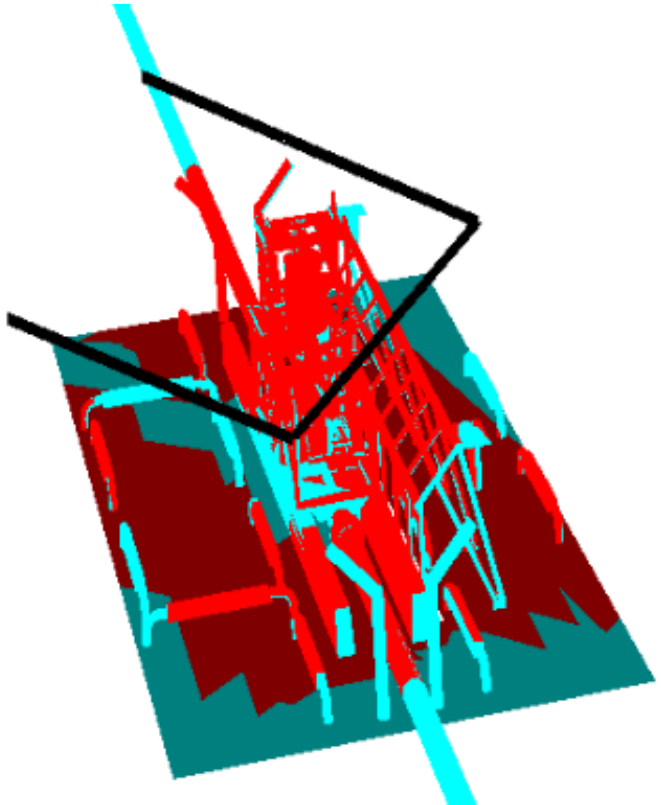


1. Decode genotype into plan
2. Estimate energy usage

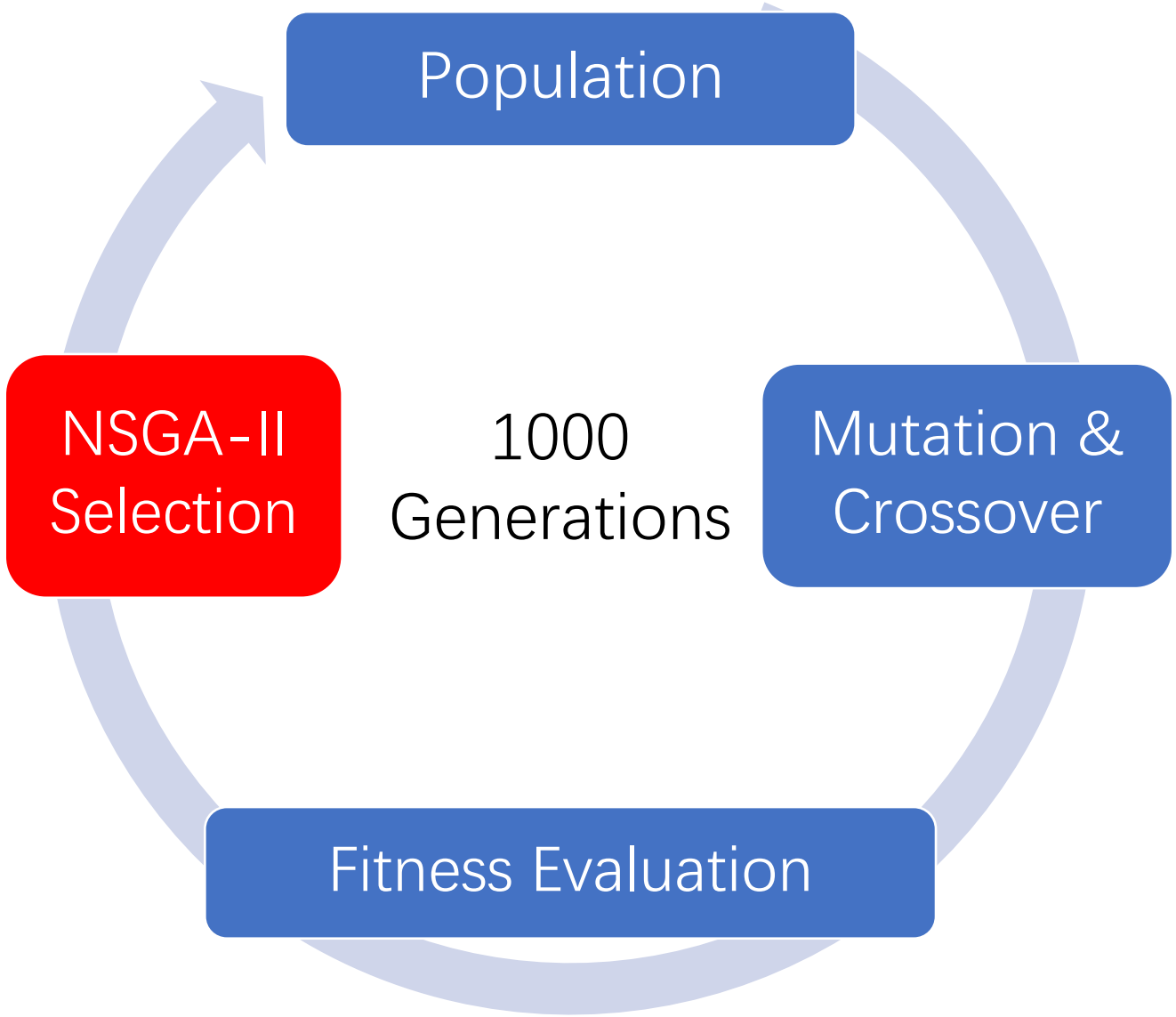
$$\sum_{\vec{e} \in Edges(plan)} (w_{trans} \cdot ||\vec{e}||) + (w_{rot} \cdot (1 - cos(\theta_{\vec{e}-1,\vec{e}})))$$

-Any edges introducing a collision are *penalized* by adding a constant term to their energy usage





1. Decode genotype into plan
2. Calculate energy usage
3. Estimate coverage:
   - Estimate all geometric primitives covered by each edge in the plan
   - Calculate the total area of covered primitives
   - Coverage score : $1.0 - (covered_area/total_area)$


Population
Mutation &
Crossover
Fitness Evaluation
NSGA-II
Selection
1000
Generations

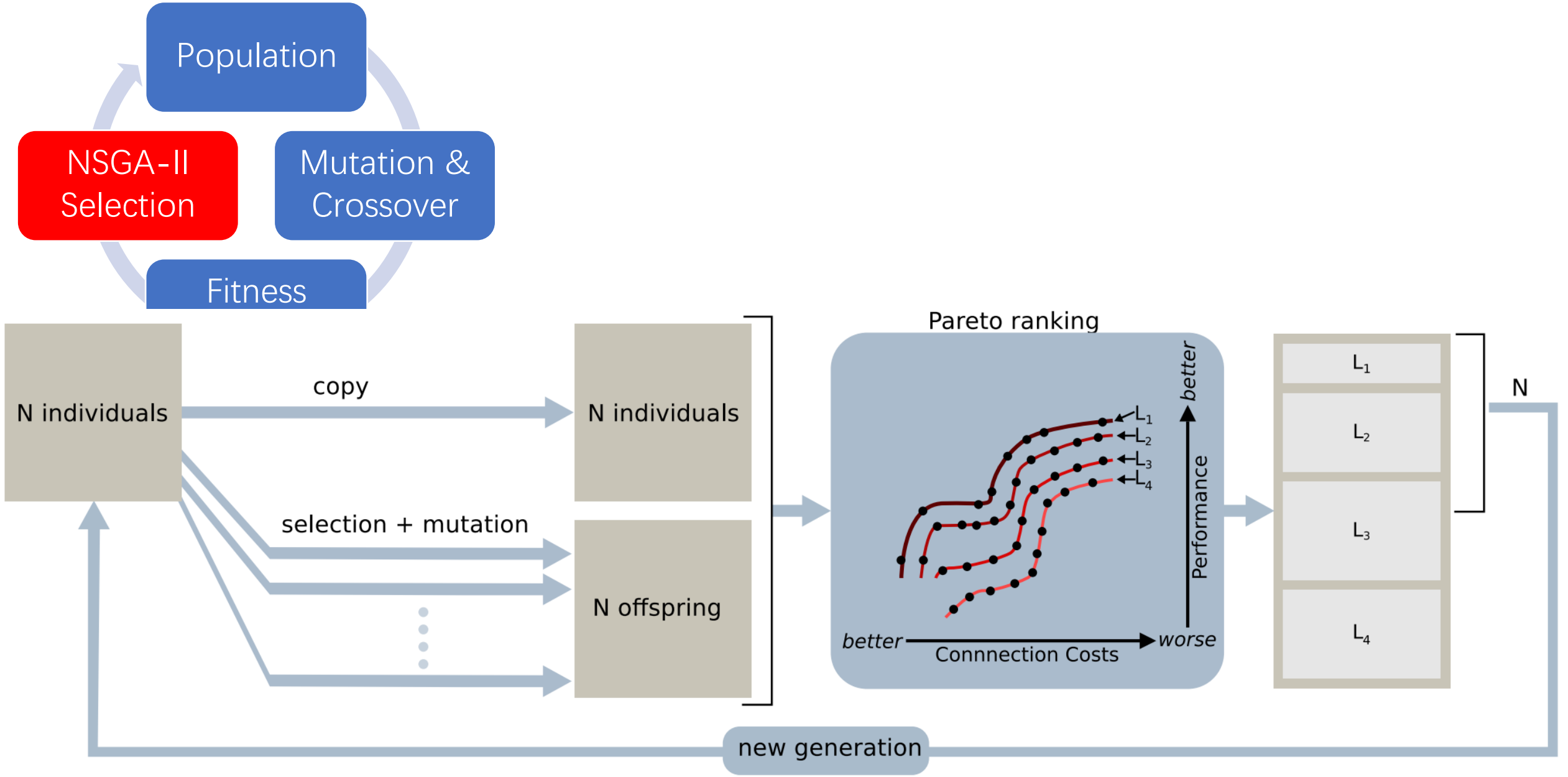


Figure from:

The evolutionary origins of modularity

Jeff Clune ✉, Jean-Baptiste Mouret and Hod Lipson

Published: 22 March 2013 | https://doi.org/10.1098/rspb.2012.2863

Which of the L3-individuals should we keep?

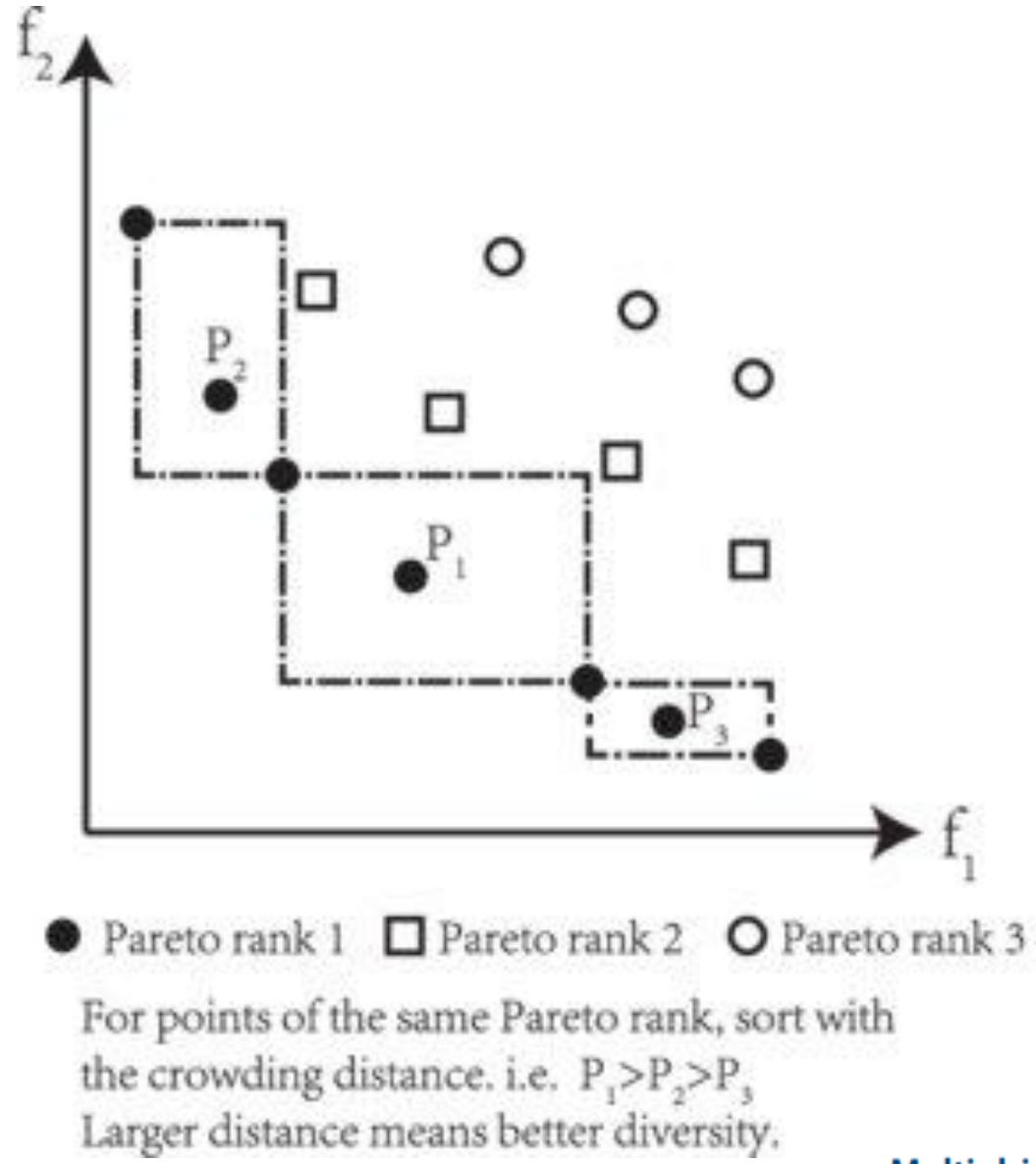


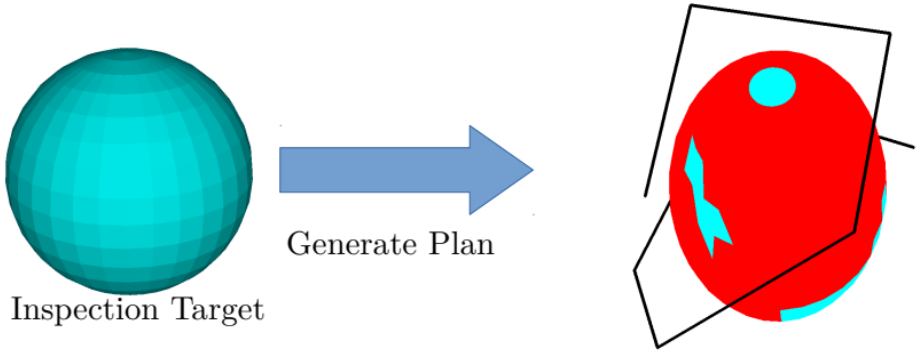
Figure from:

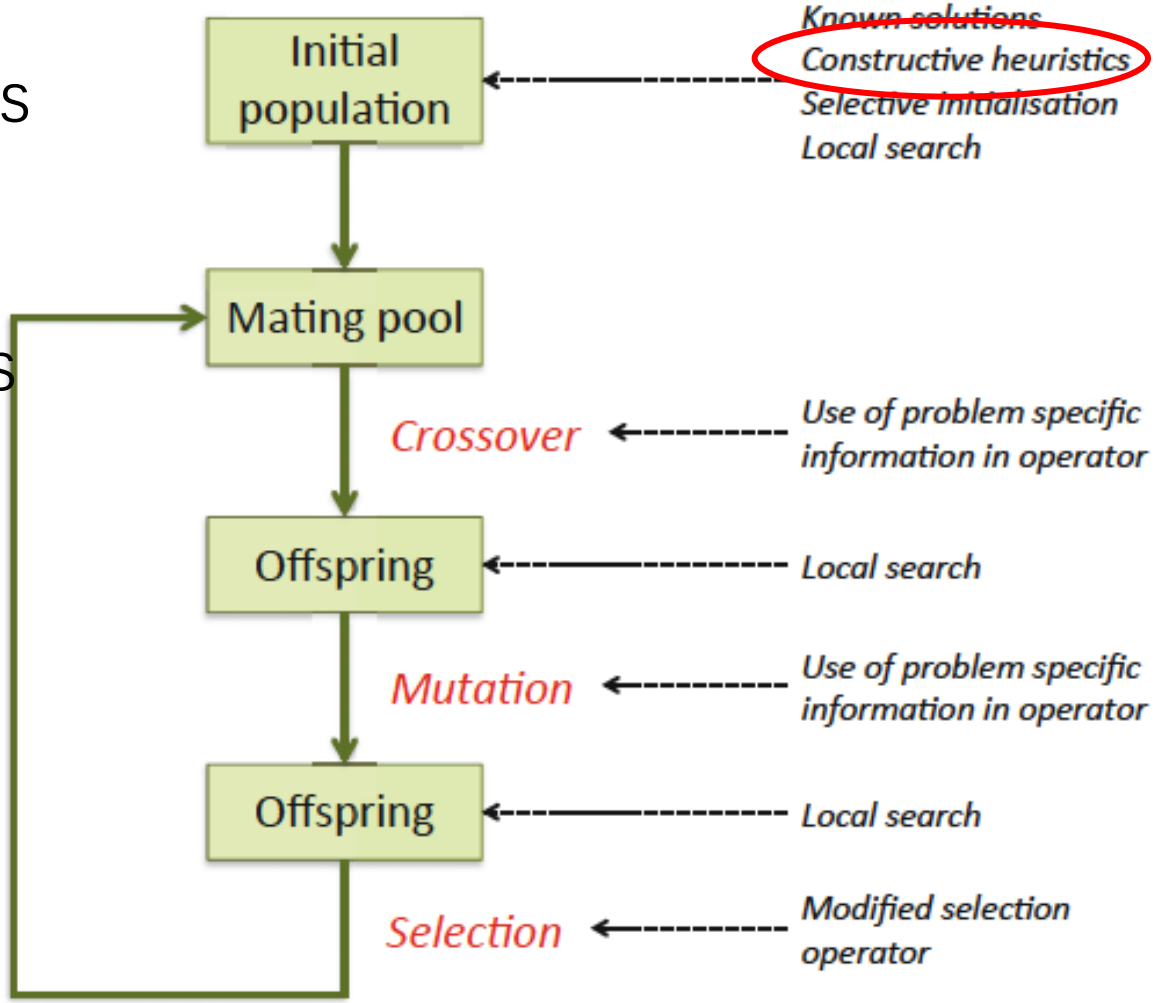
Multiobjective adaptive surrogate modeling-based optimization for parameter estimation of large, complex geophysical models

Wei Gong[1,2], Qingyun Duan[1,2], Jianduo Li[1,2], Chen Wang[1,2], Zhenhua Di[1,2], Aizhong Ye[1,2], Chiyuan Miao[1,2], and Yongjiu Dai[1,2]

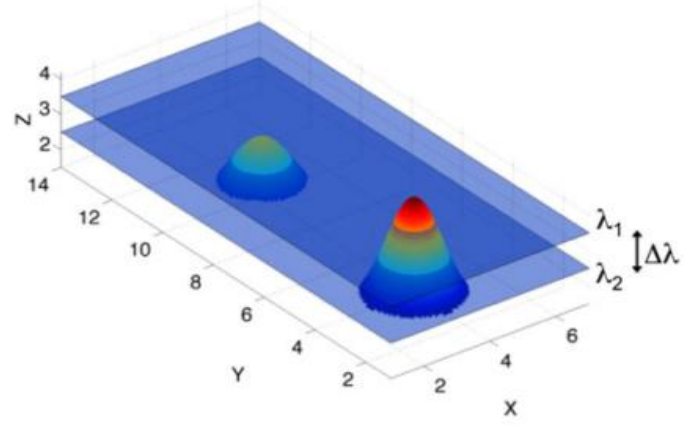
Hybridization - Constructive Heuristics

- Idea: Find examples of OK plans to **seed** the initial population
- The plans don't have to be great, just better starting points than random plans
- **What could be a simple, OK plan for inspections?**

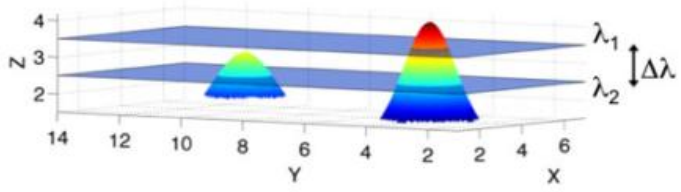




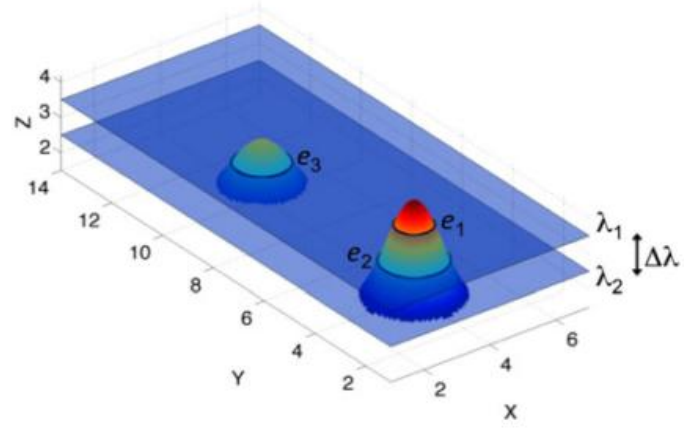
My idea: Make simple, circling solutions



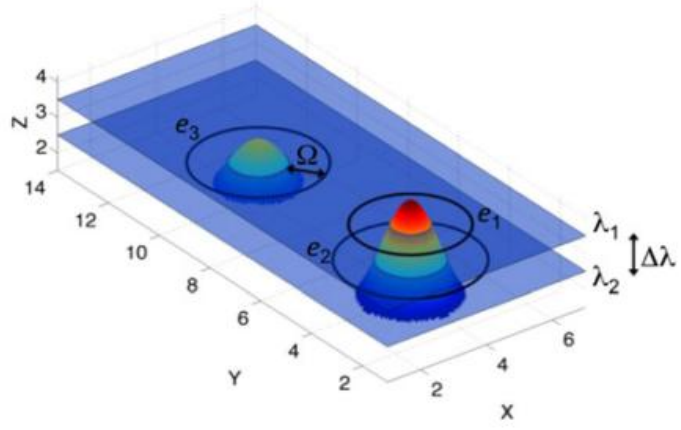
(a) Slice planes (slanted view).



(b) Slice planes (side view).

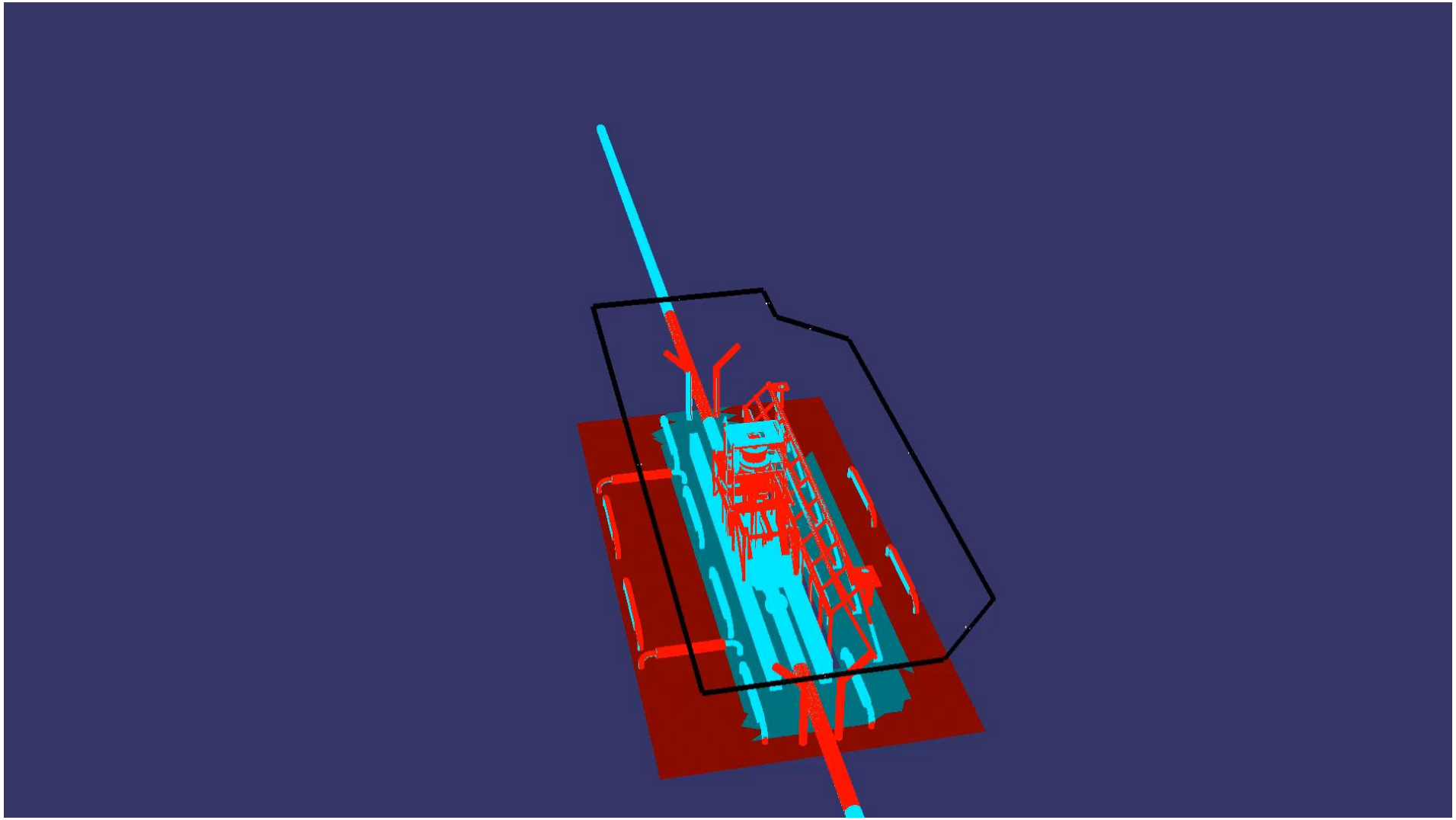


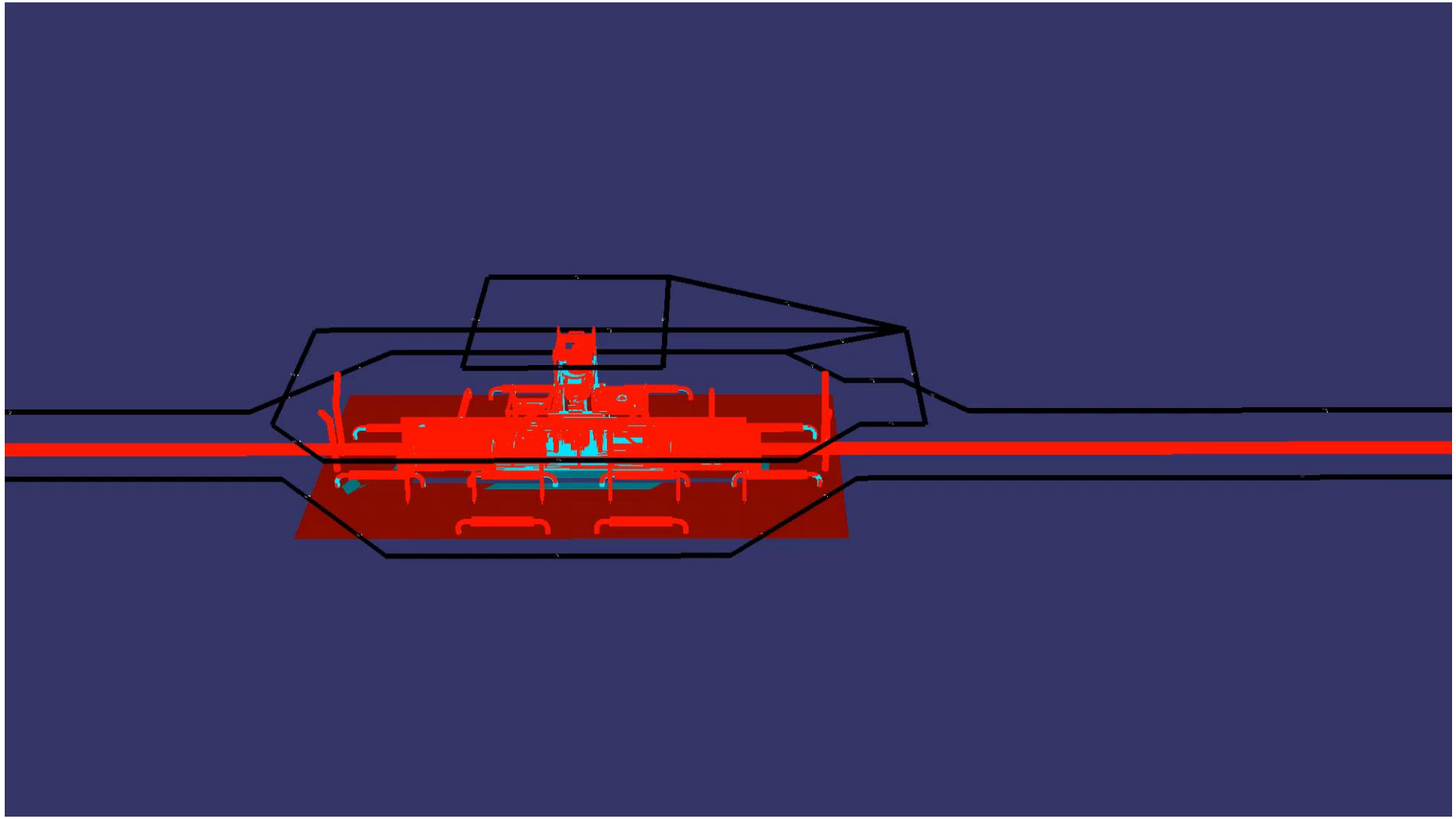
(c) Intersection edges (see Algorithm 1, line 4).

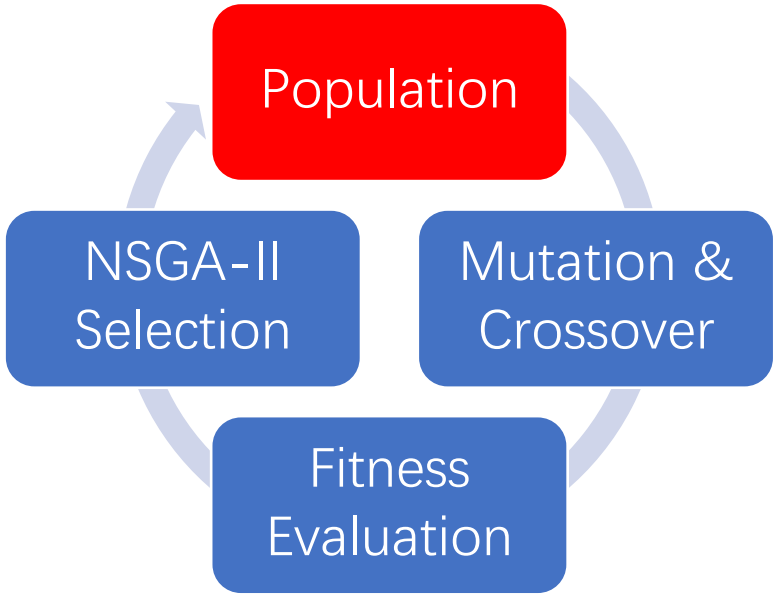


(d) Offset edges (see Algorithm 1, line 6).

E. Galceran, R. Campos, Narcis Palomeras, D. Ribas, M. Carreras, and P. Ridao. Coverage Path Planning with Real-time Replanning and Surface Reconstruction for Inspection of Three-dimensional Underwater Structures using Autonomous Underwater Vehicles. *Journal of Field Robotics*, 32(7):952–983, 2014.



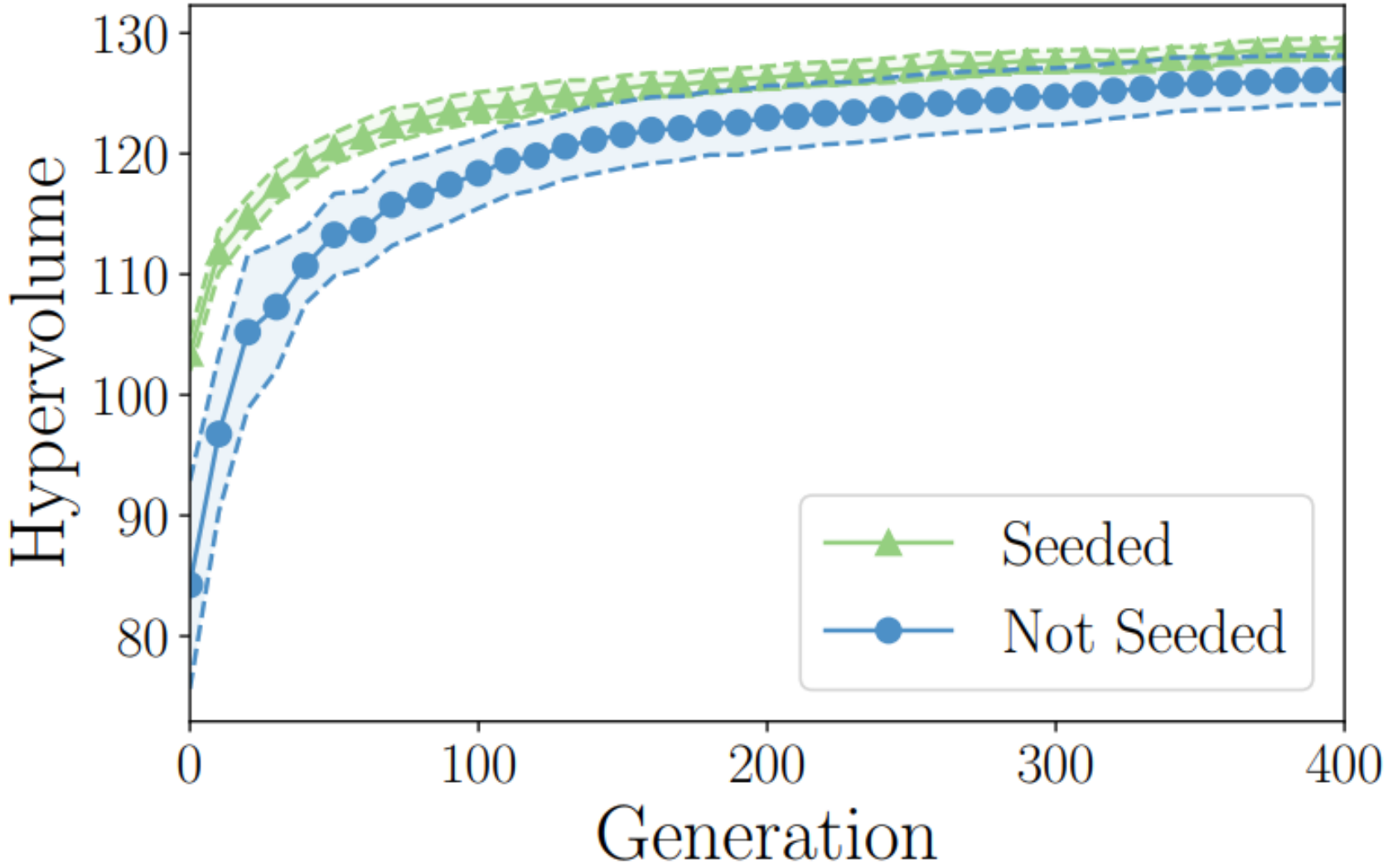




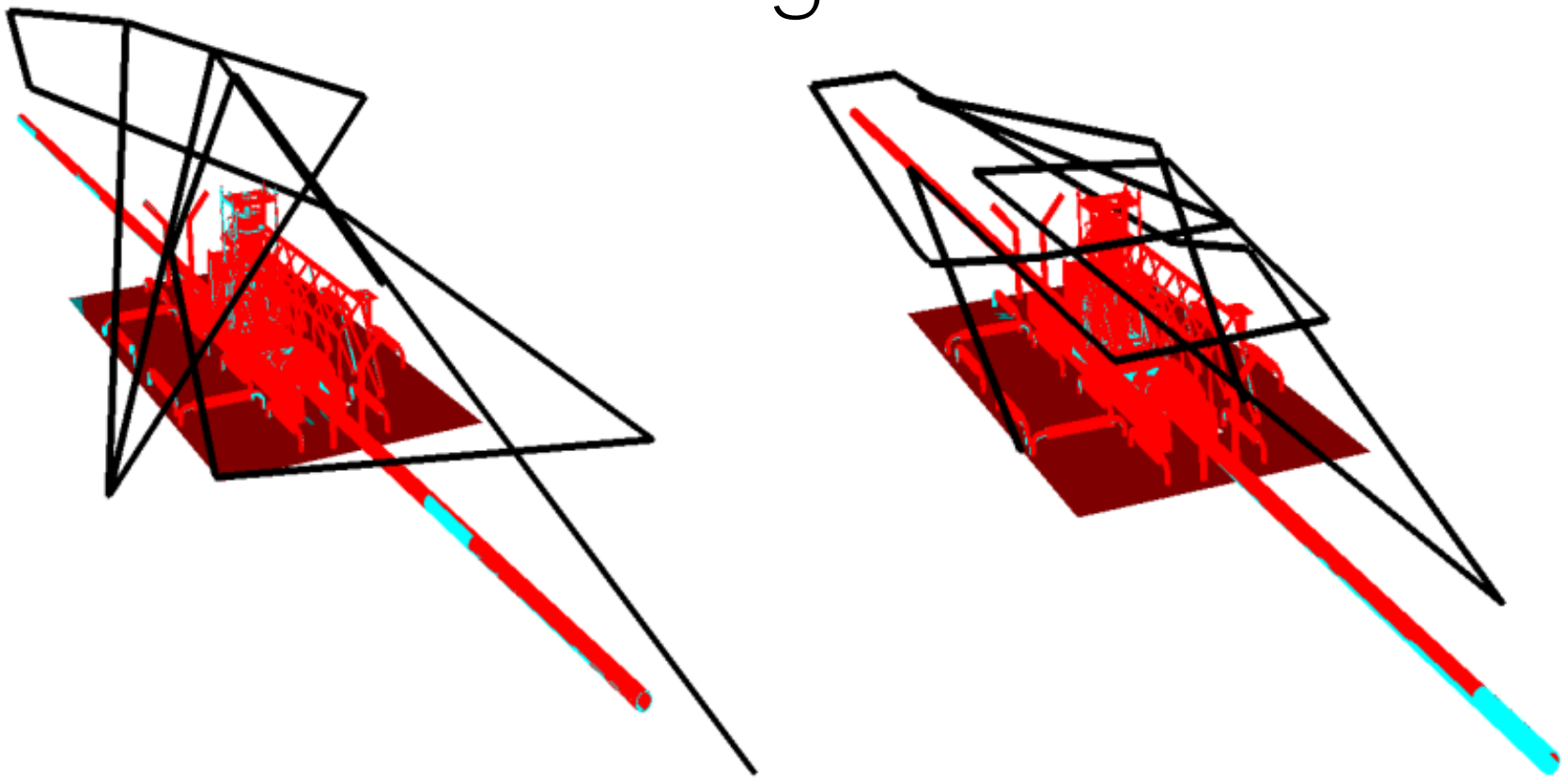
- 40 individuals
- Initialization:
  - 65% random valid genotypes
  - 35% seeded with **reasonable** solutions

Did this kind of seeding work?

Did this kind of seeding work?



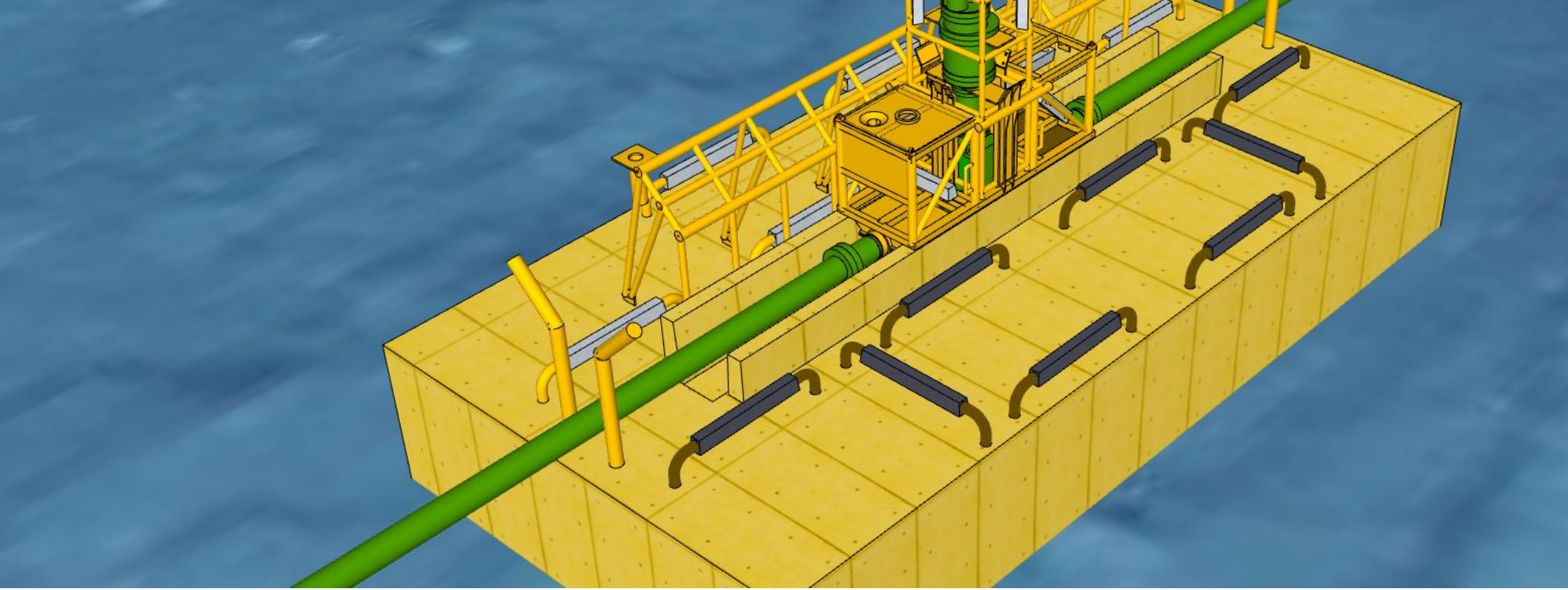
Did this kind of seeding work?



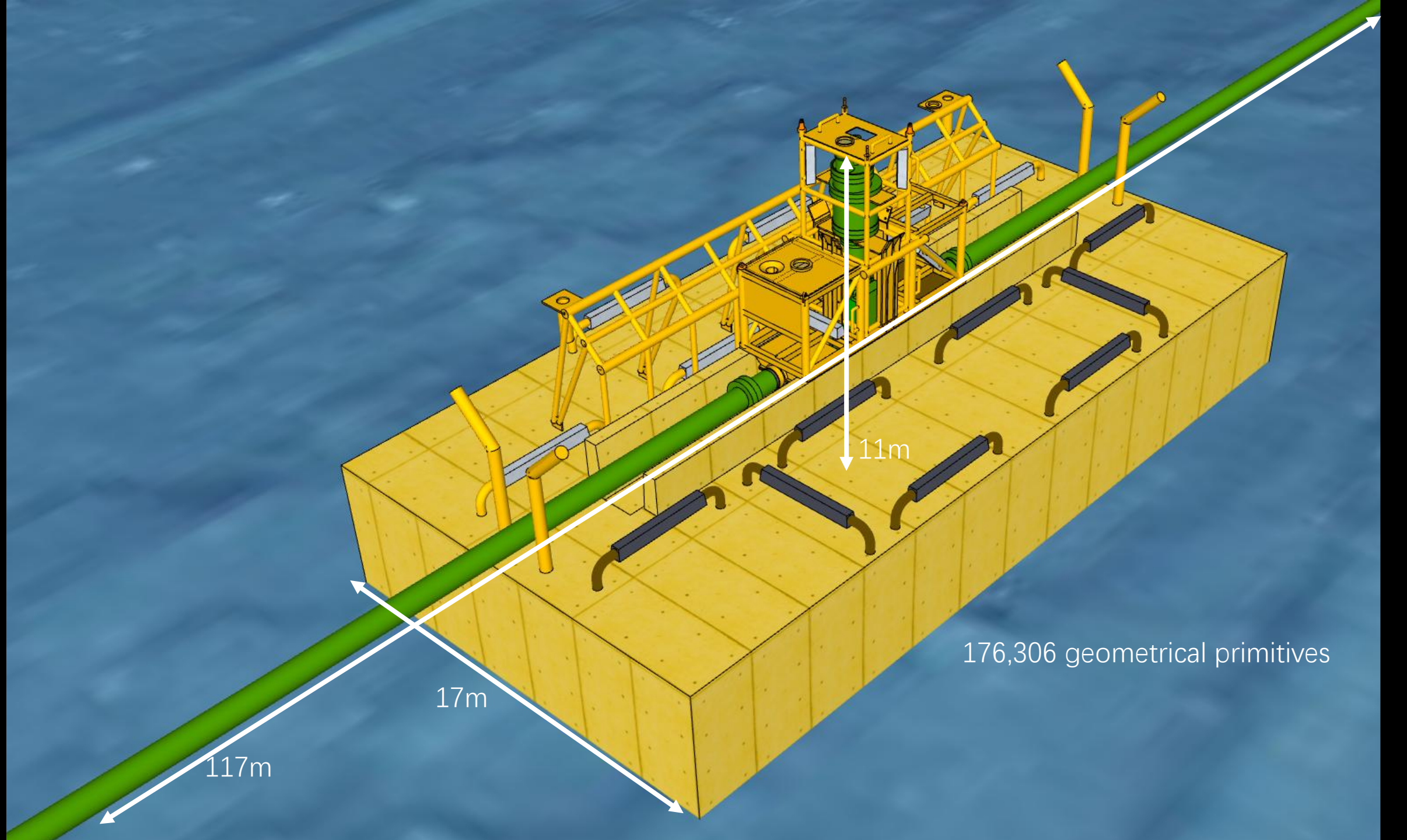
(a) Plan evolved without seeding – scores (0.23, 71.9).

(b) Plan evolved with seeding – scores (0.21, 73.2).

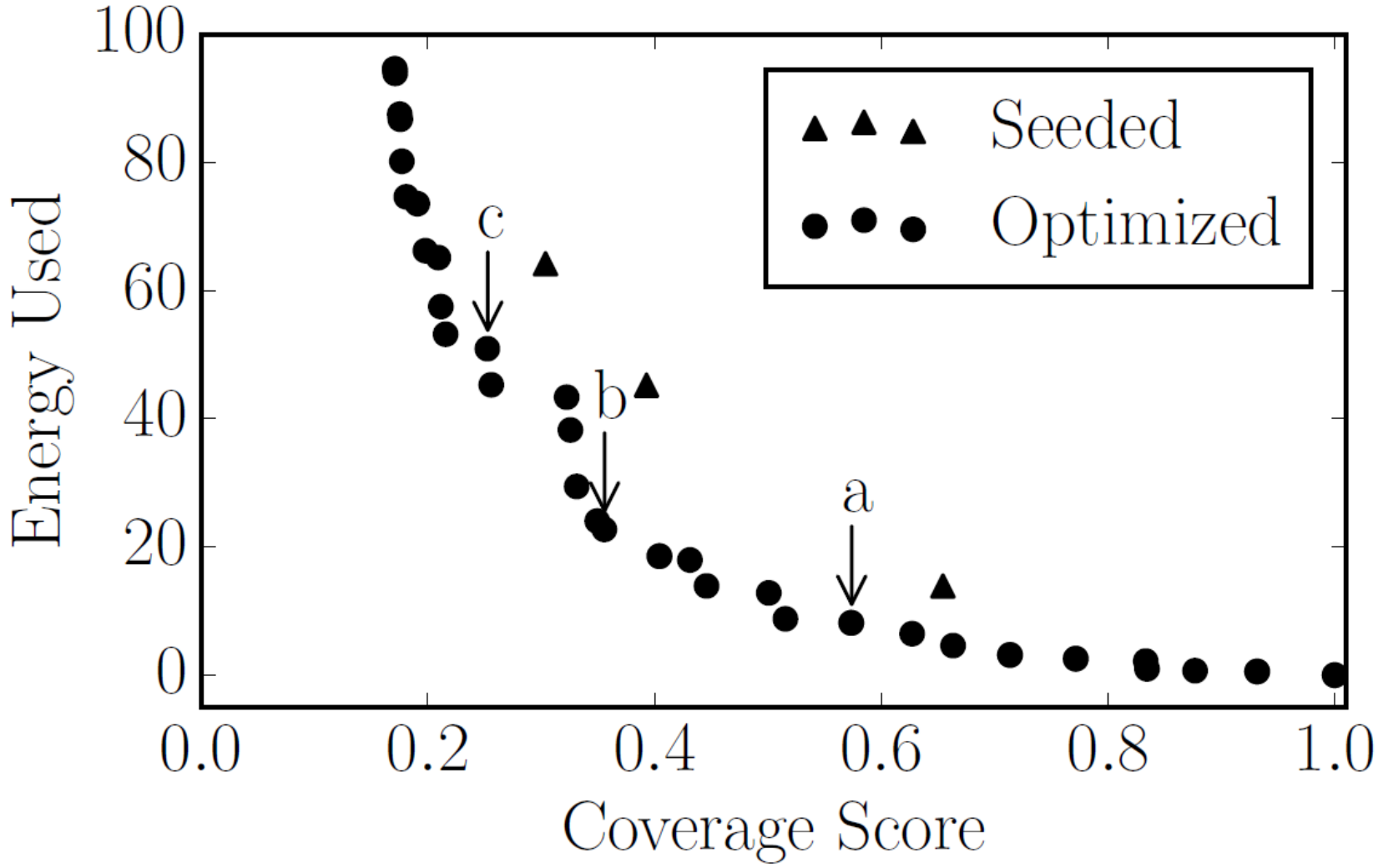
Figure 14: **The results on evolved plan structure of seeding.** When seeding (right), evolved plans retain much of the clean structures of the seed plans, whereas evolutionary runs without seeding (left) have a more irregular structure.

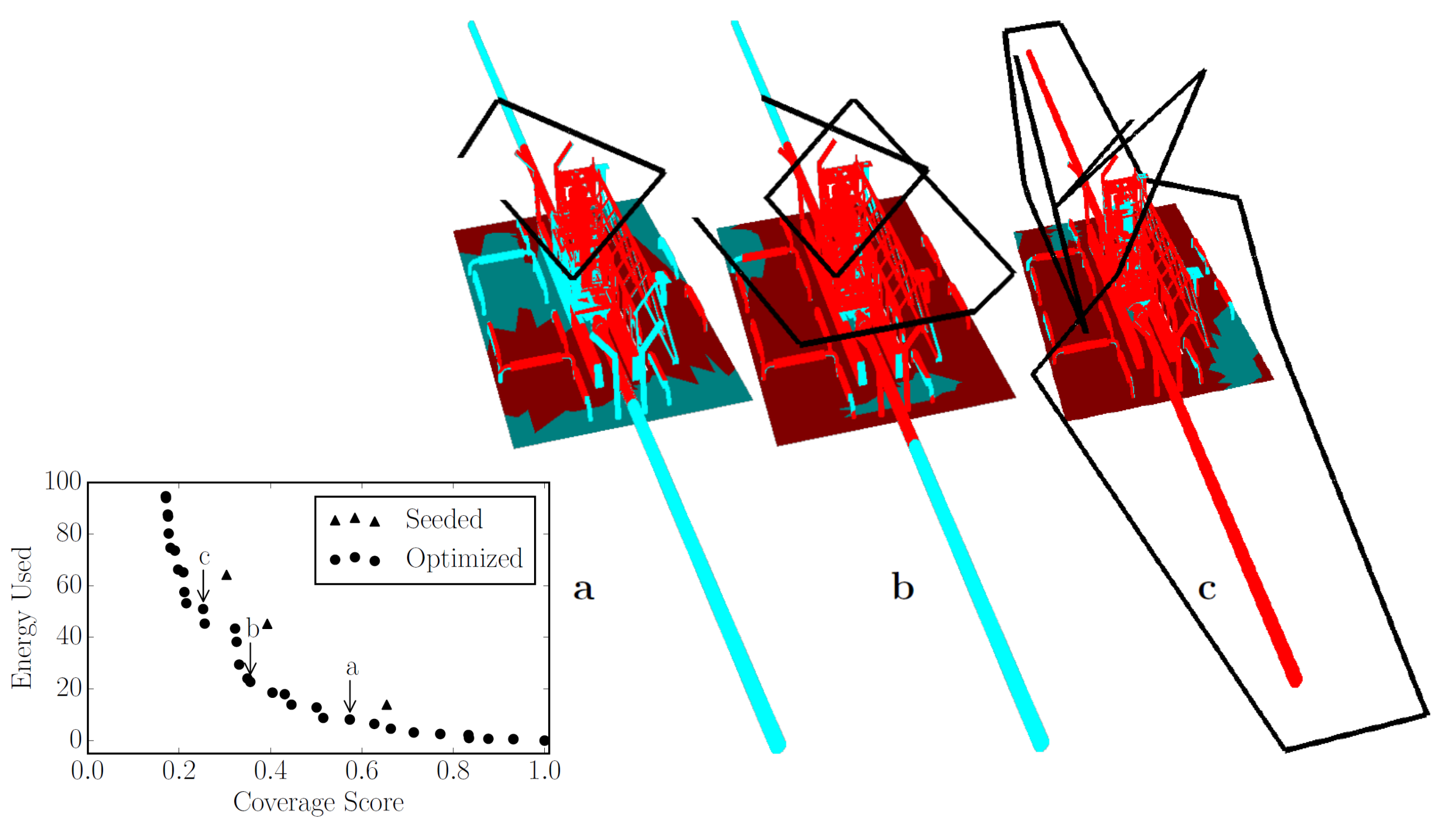


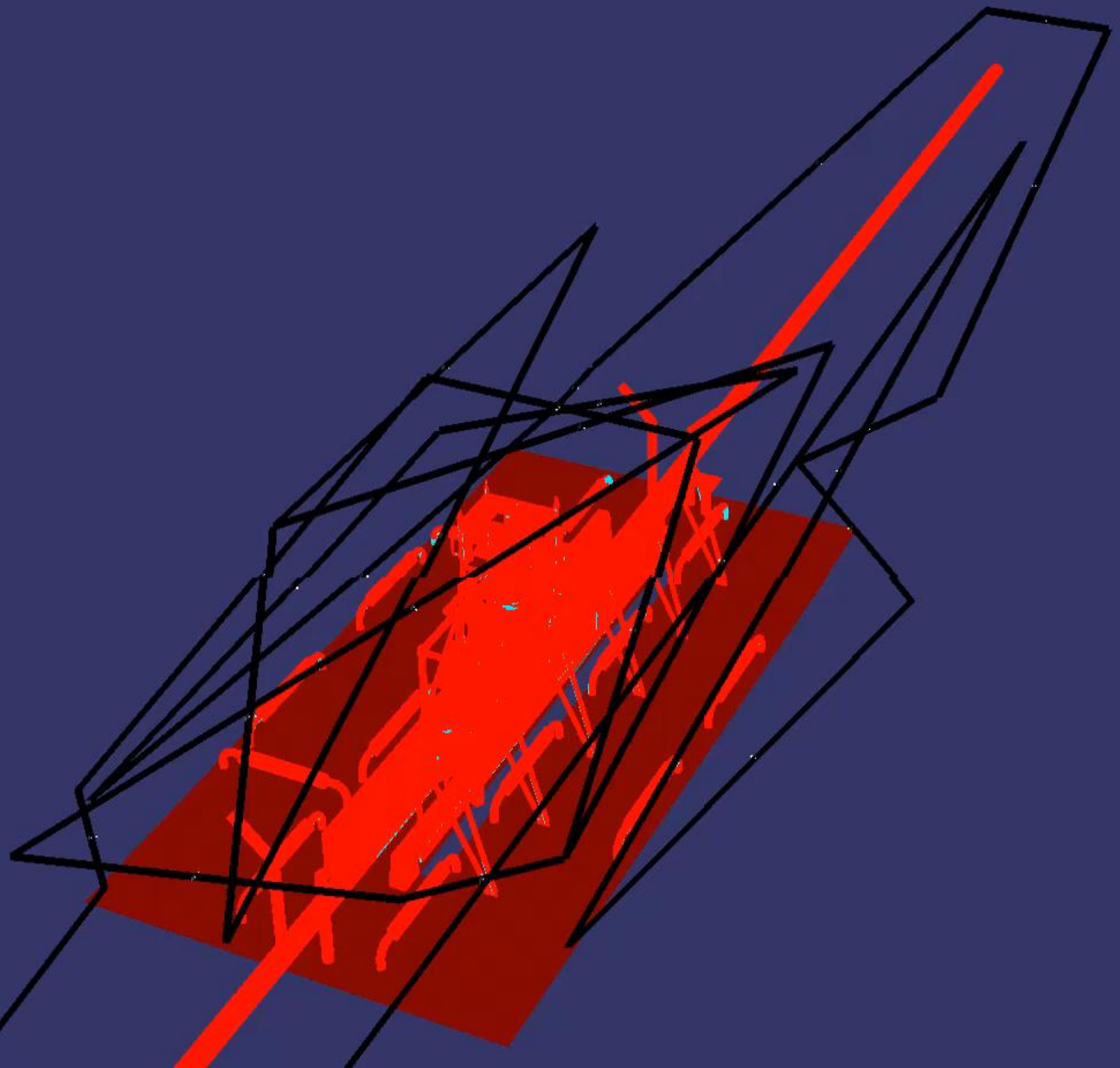
Evaluation Tests

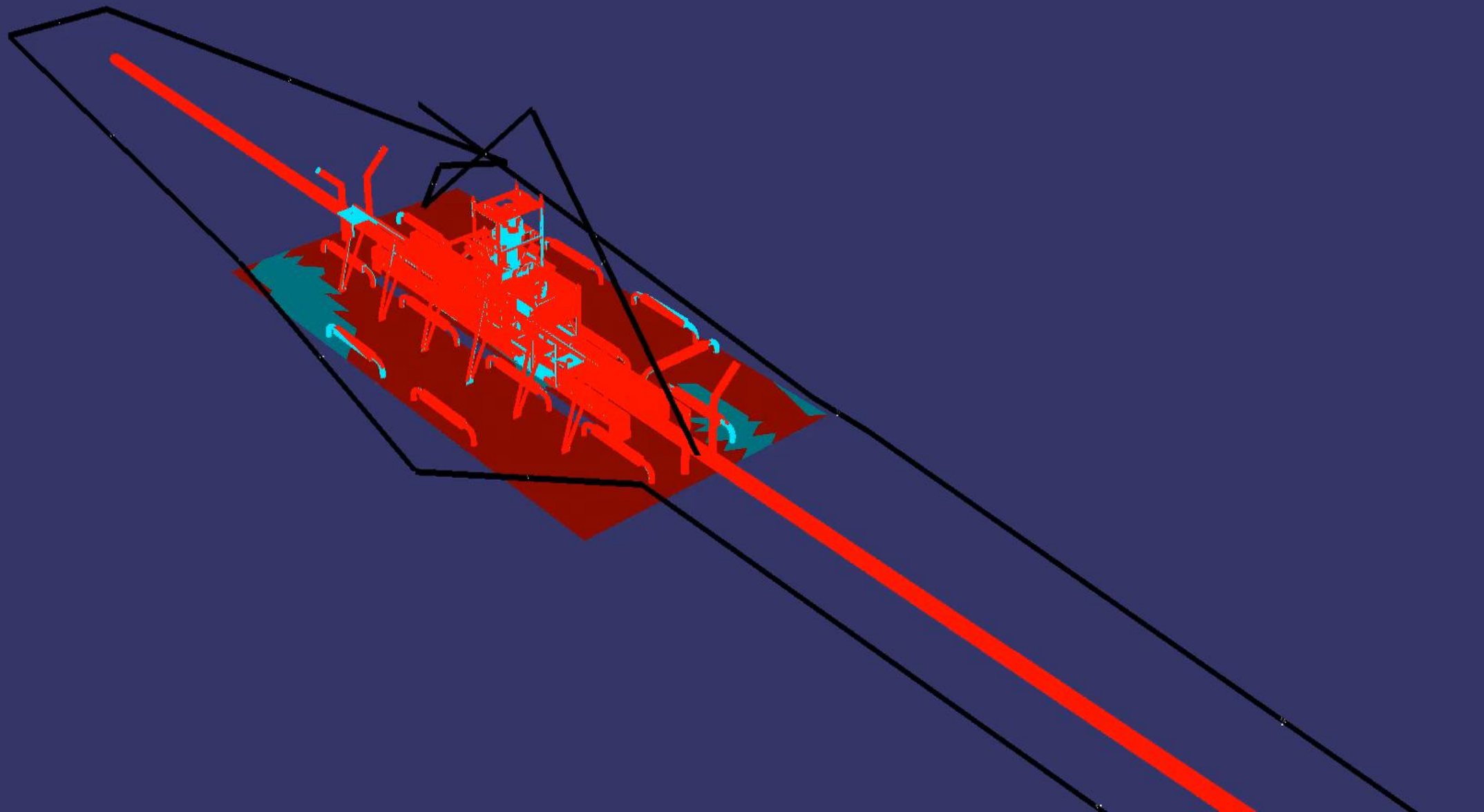

11m
17m
117m
176,306 geometrical primitives

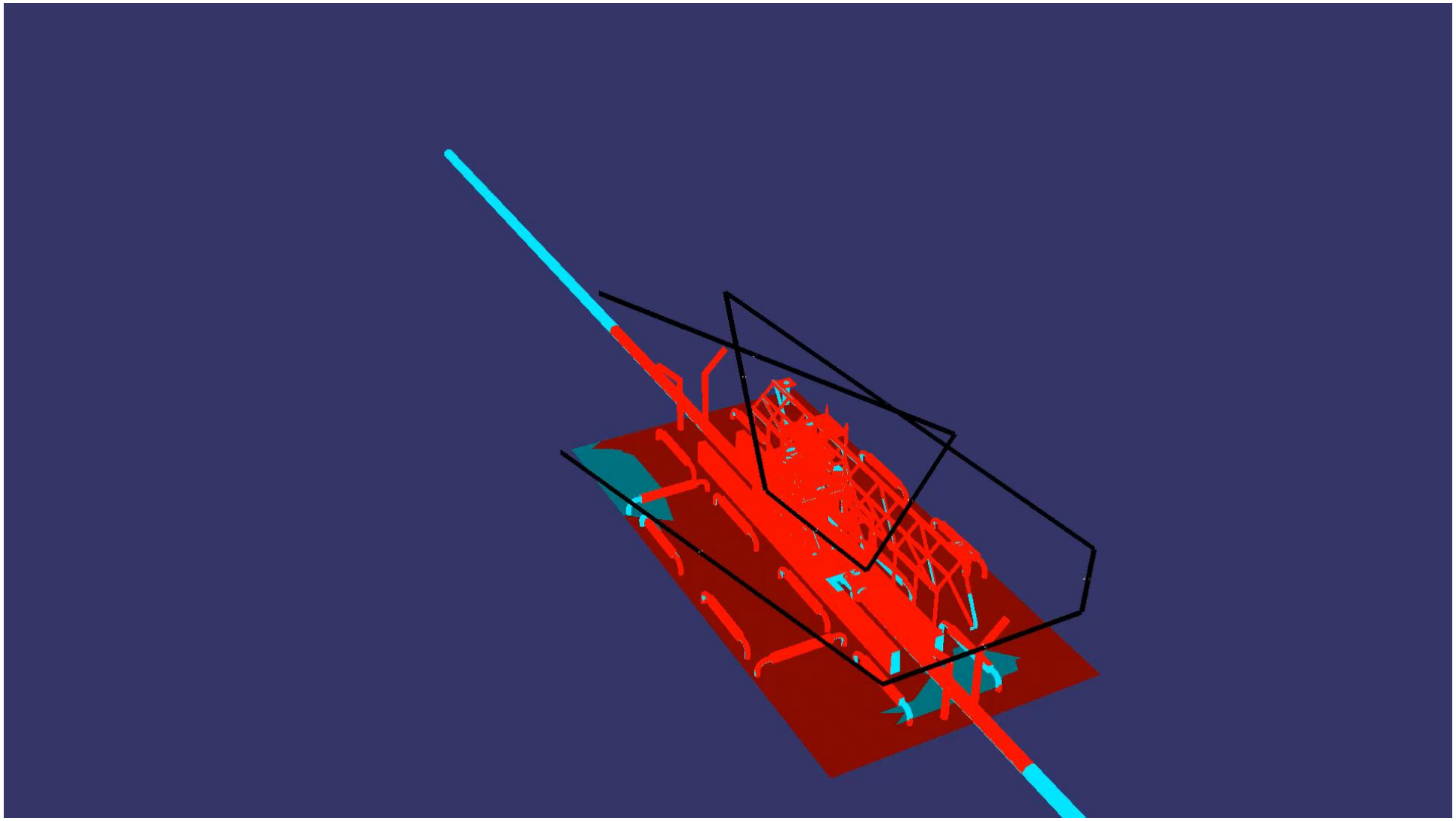
After 1000 Generations of NSGA-II

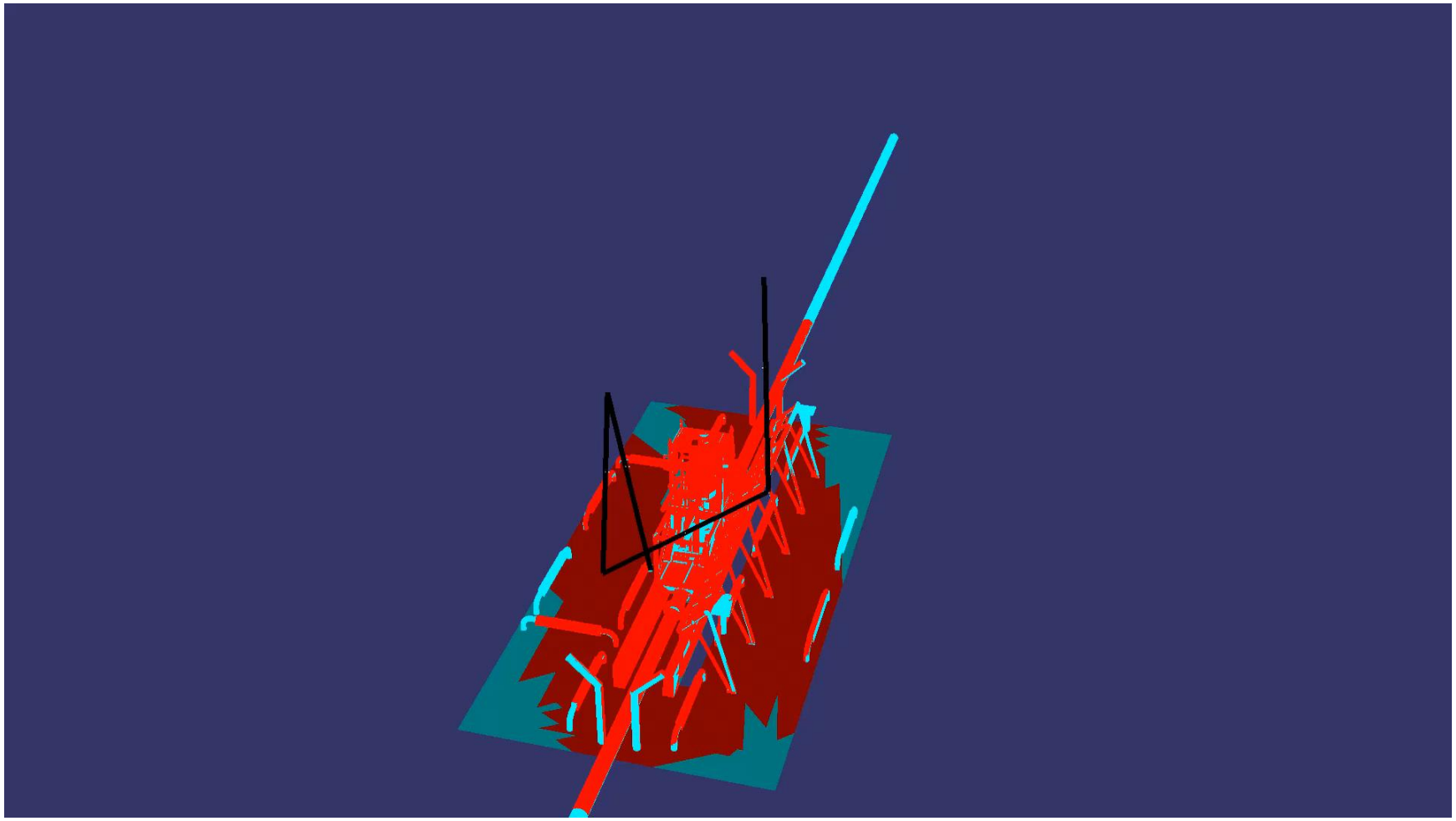



Seeded
Optimized
Energy Used
Coverage Score
0
20
40
60
80
100
0.0
0.2
0.4
0.6
0.8
1.0
a
b
c
a
b
c



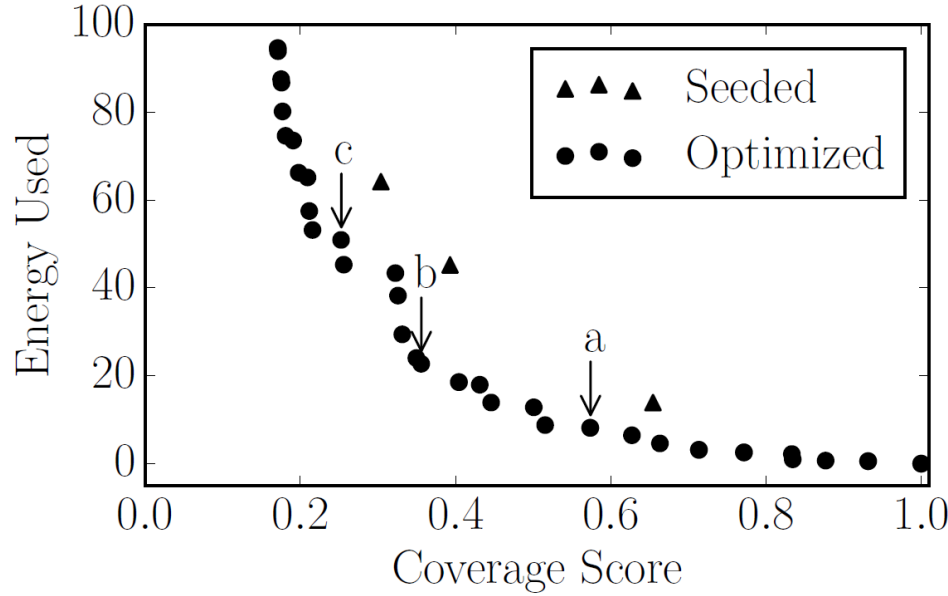


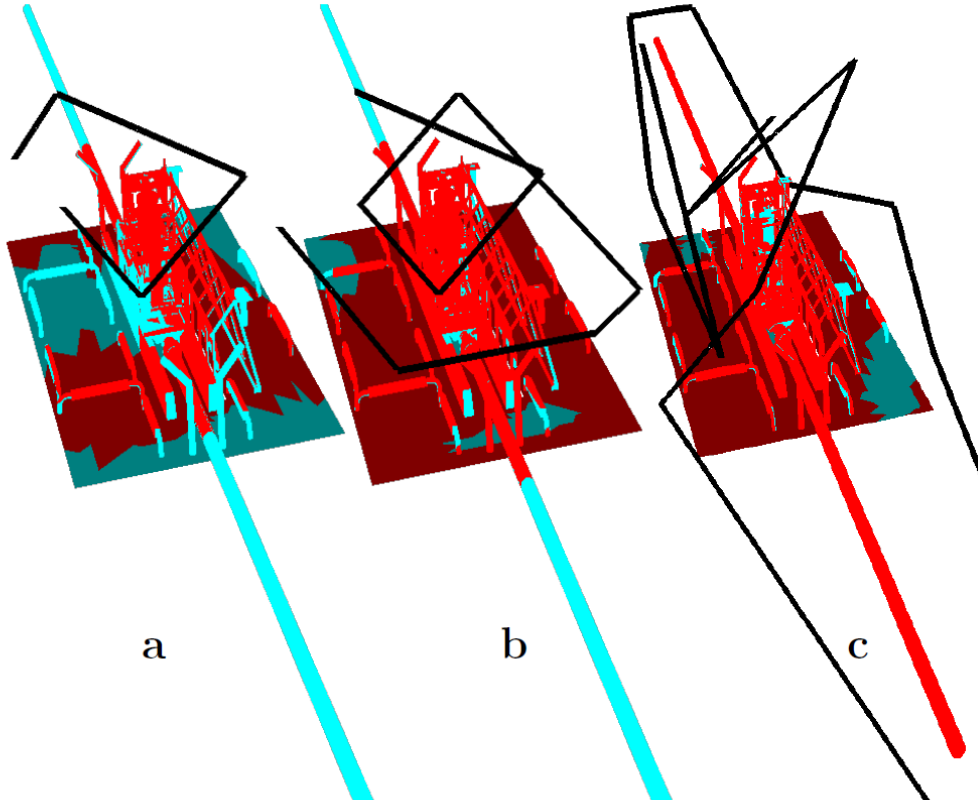




Summarizing

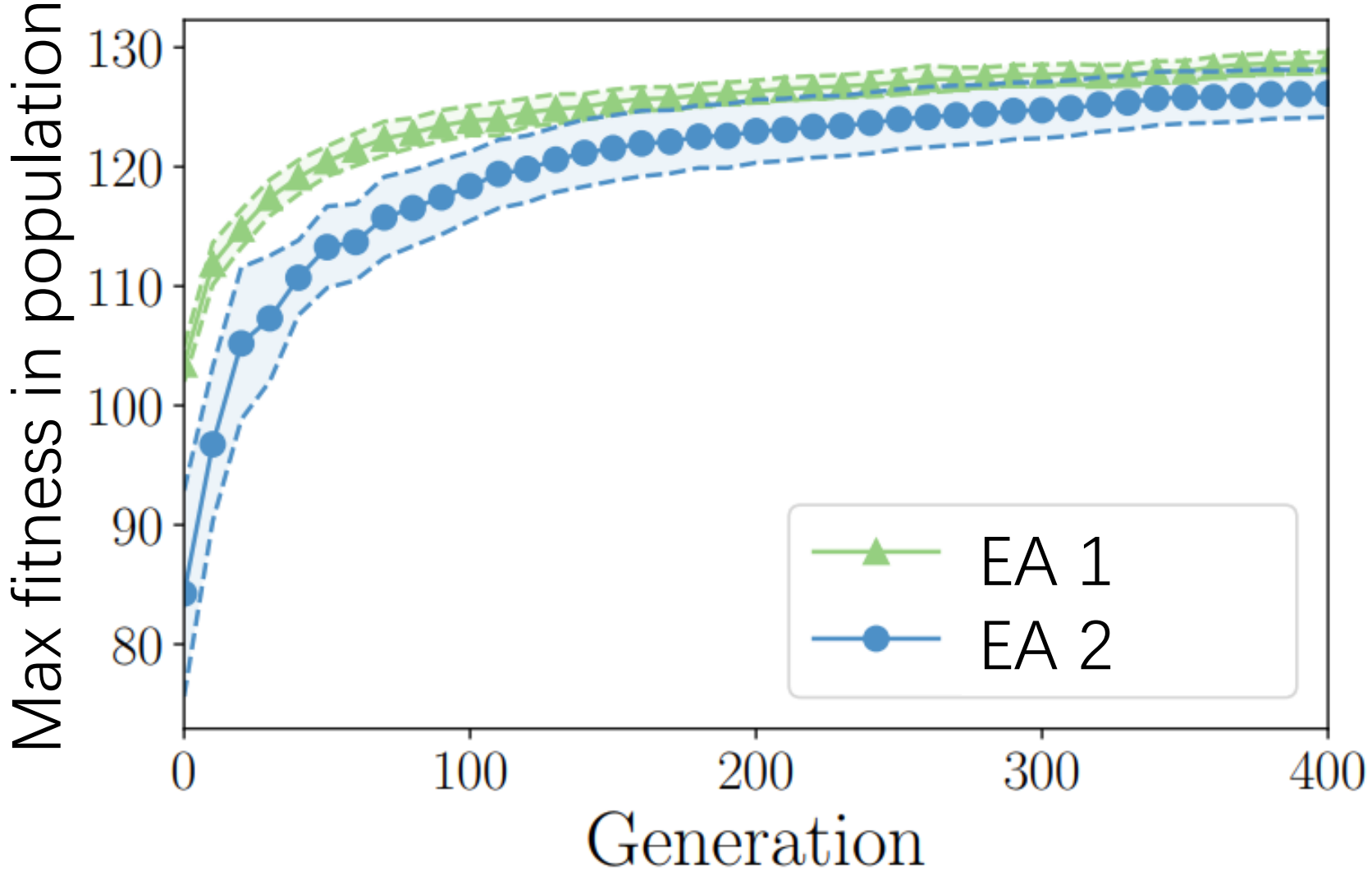
- Multiobjective EAs:
  - State-of-the-art for many kinds of multiobjective optimization
  - Gives us a **diverse** collection of solutions, lets us choose **according to our needs**
- Hybridization: Helps speed up our EA with **domain knowledge**





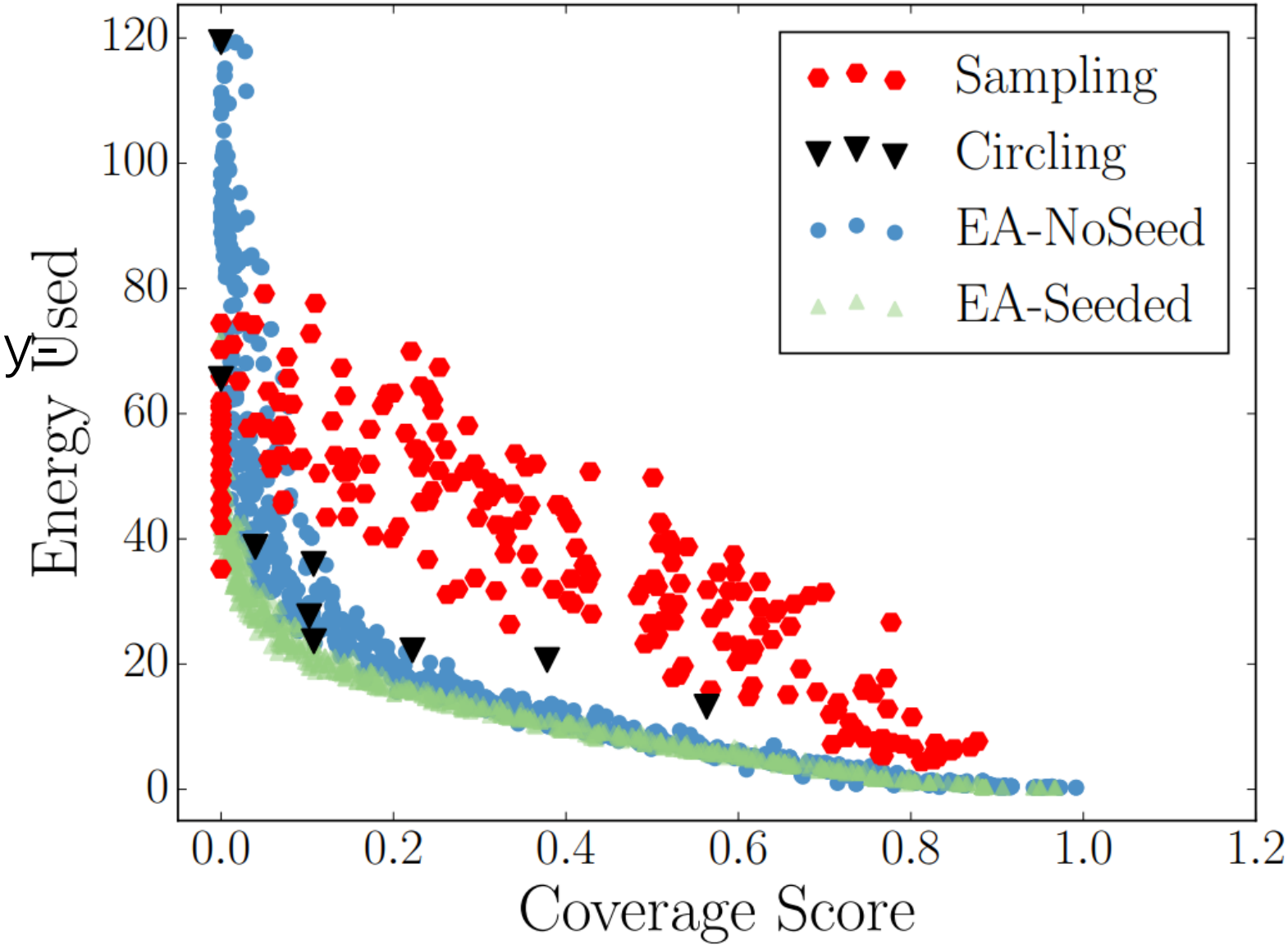
Questions?

Comparing Single-objective Optimization algorithms: Easy



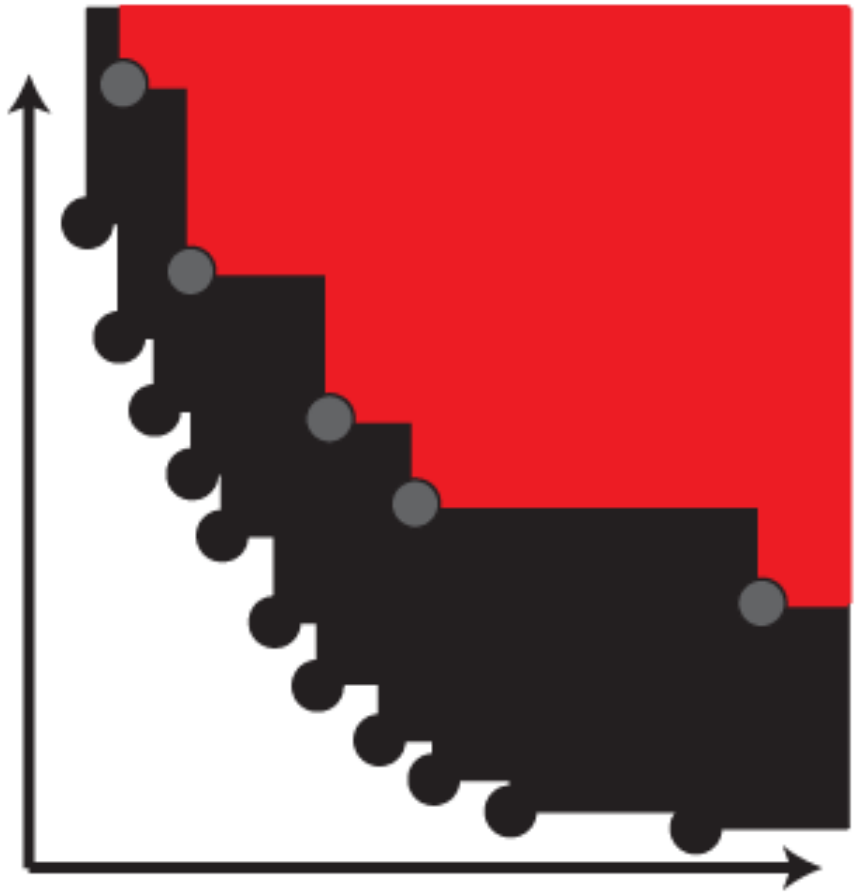
Comparing MOEA runs: How?

- Which of two populations (blue, green) is better?
- Note: Both x-axis and y-axis are minimization problems
- Can we somehow *measure* which population is best?



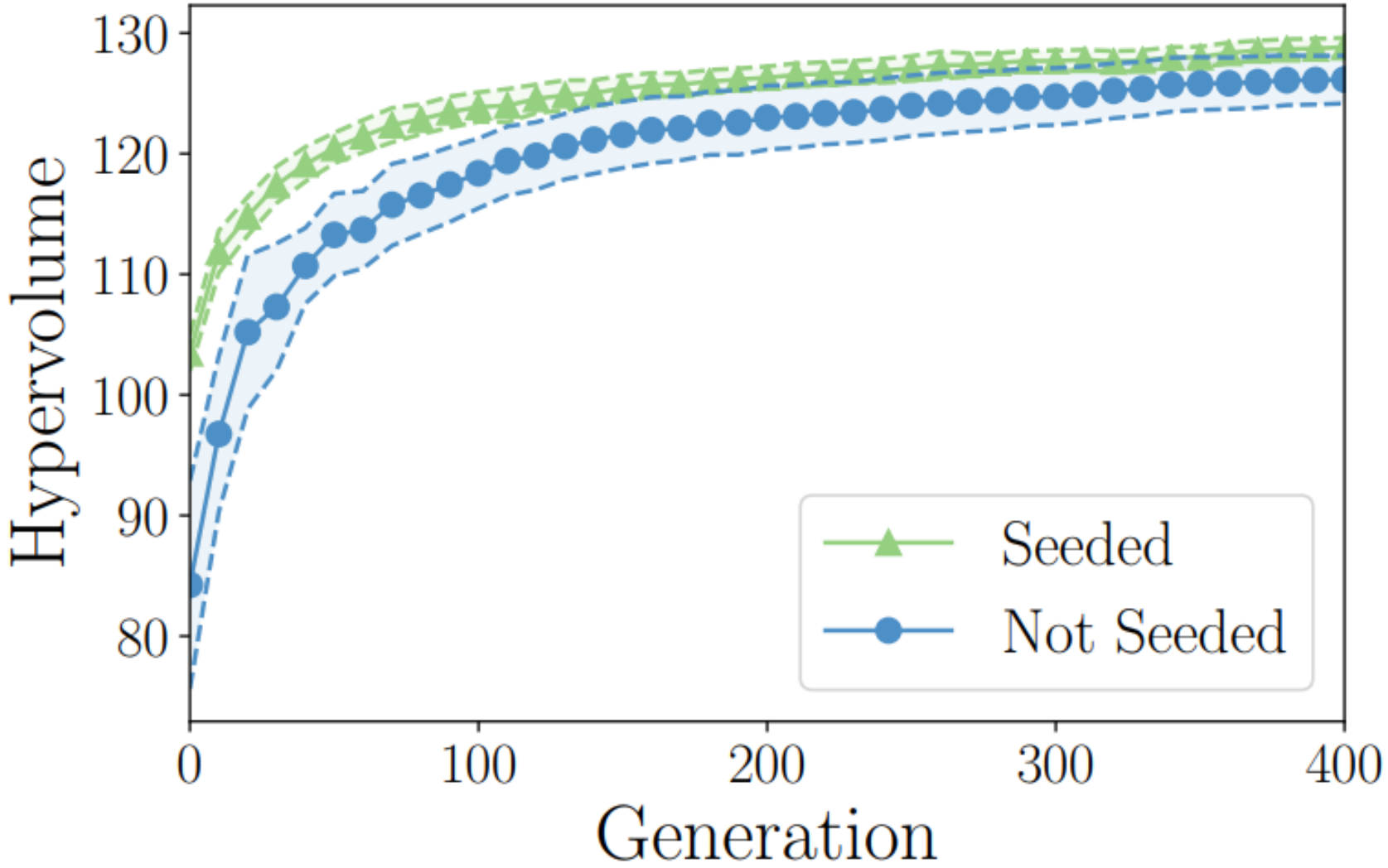
Comparing MOEA runs: The Hypervolume Indicator

- Which of two populations is better?
- Idea: Measure the "volume“ (for 2 objectives, the “area”) spanned by each population.
- Larger volume -> closer to optimum.

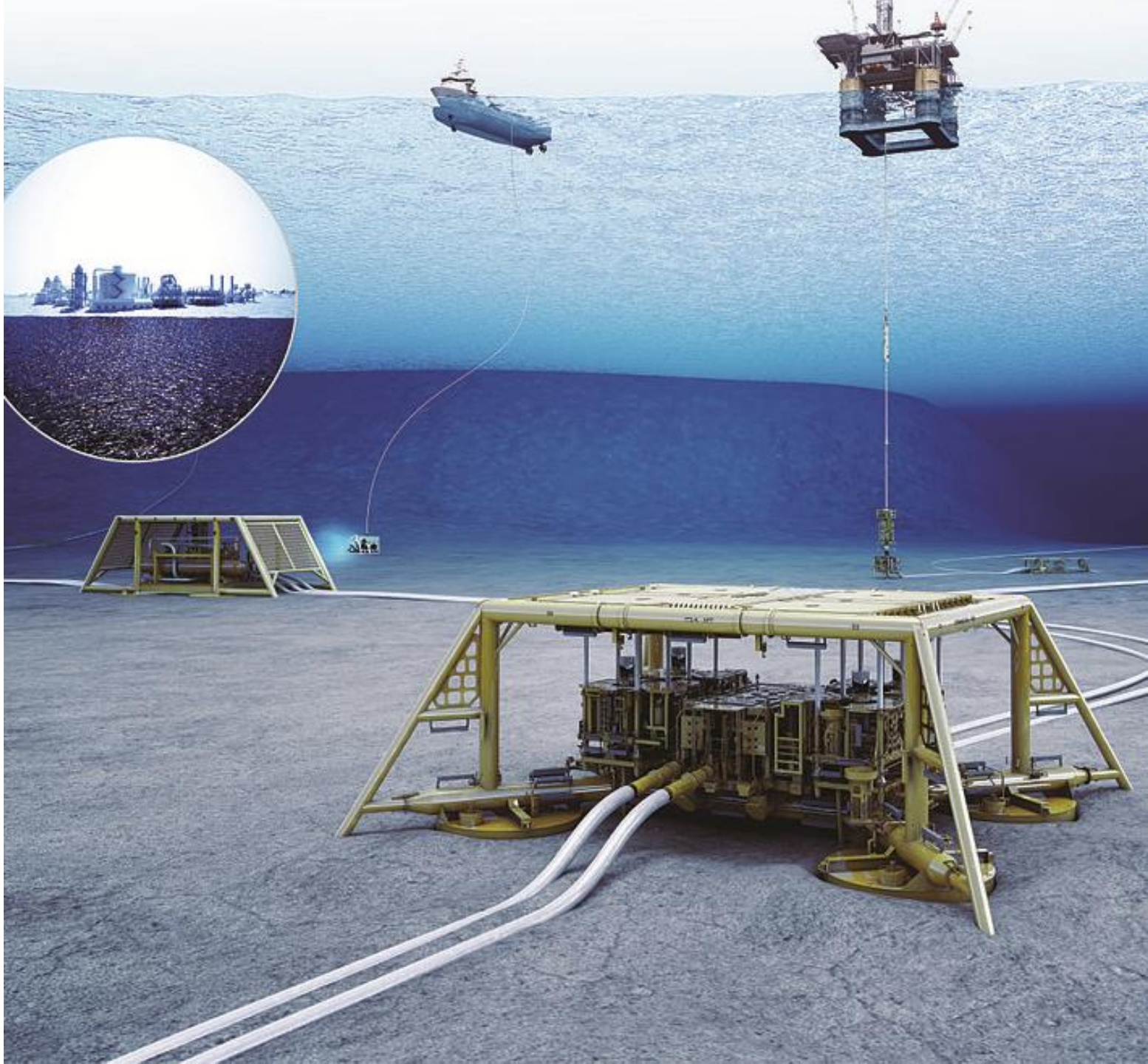


JR Kasprzyk, Water Programming: A
Collaborative Resarch Blog

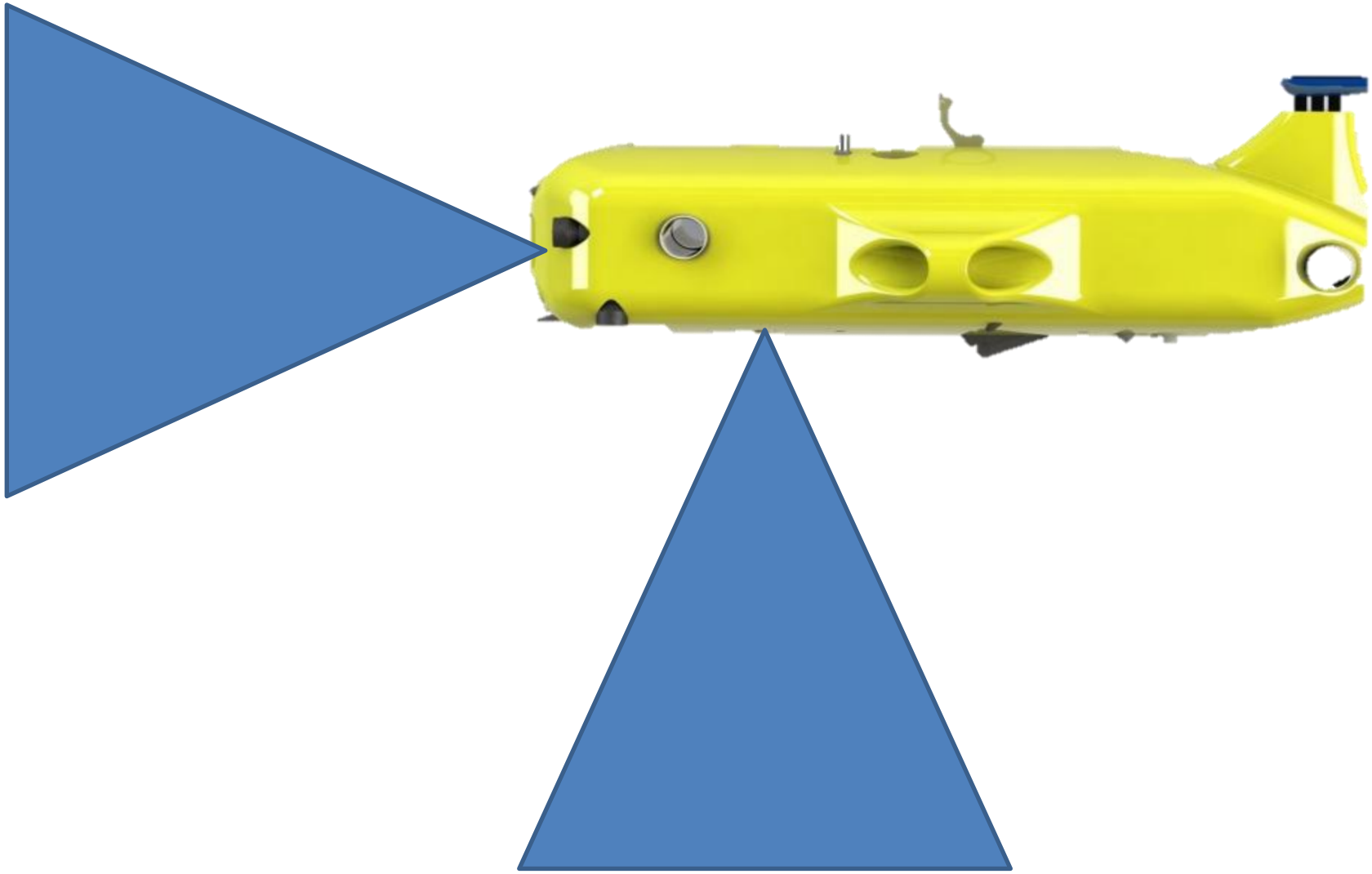
Did this kind of seeding work?



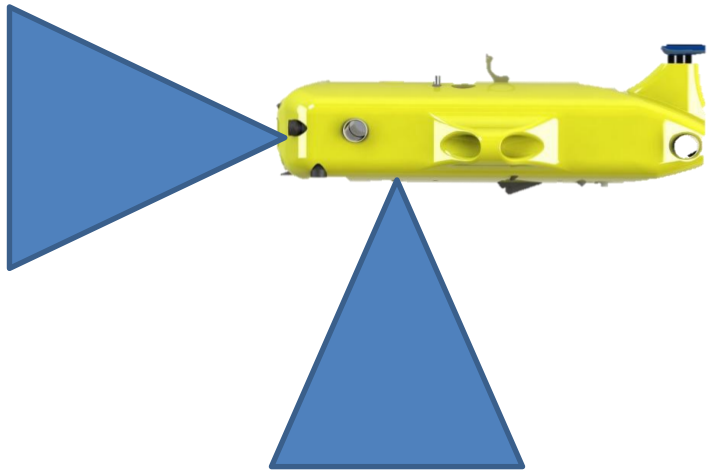
Conclusion



Dual-Camera Inspection



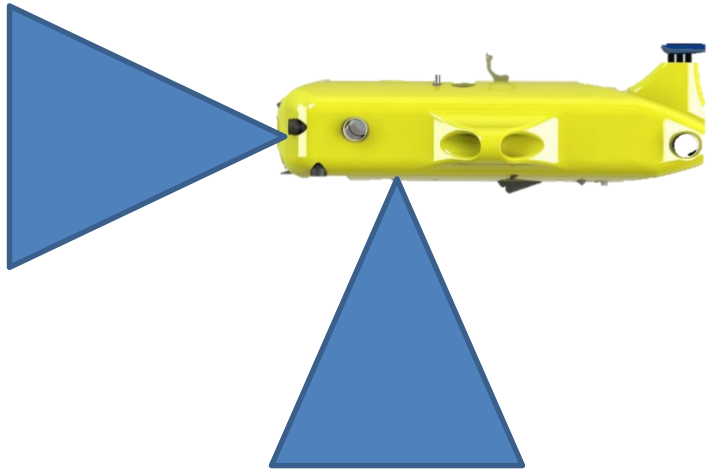
Dual-Camera Inspection



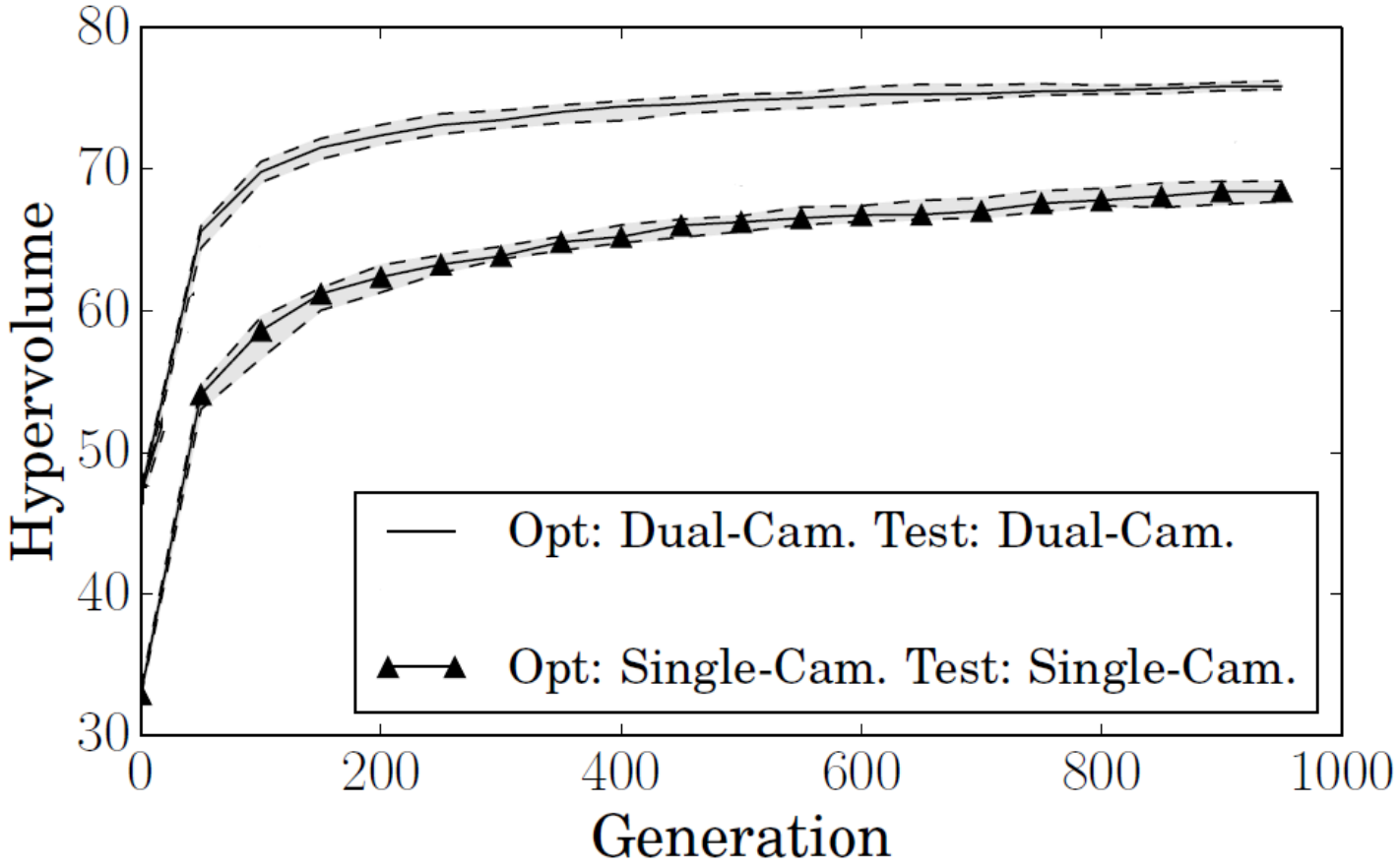
Do plans gather data more efficiently when optimized using both cameras?

I wanted to compare two runs of the algorithm, one with 1 camera one with 2

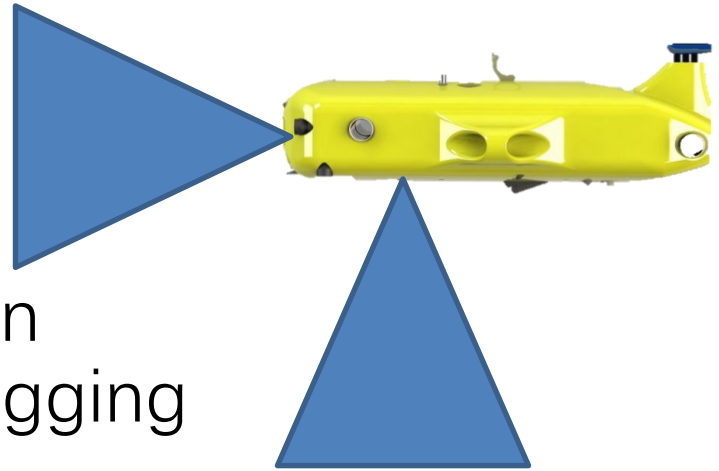
Dual-Camera Inspection



Do plans gather data more efficiently when optimized using both cameras?



Dual-Camera Inspection



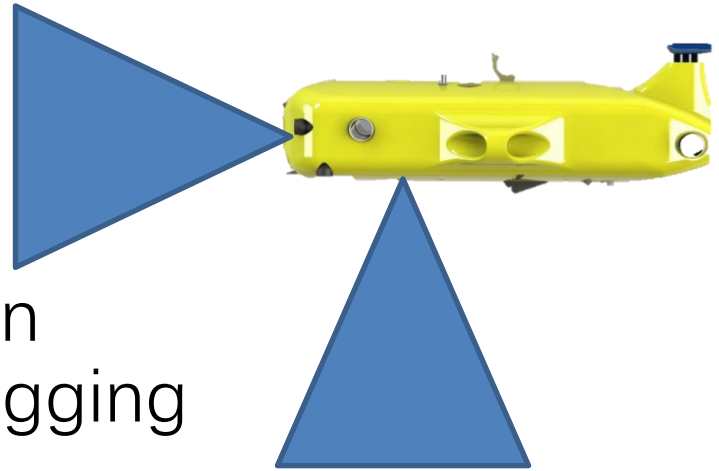
Are the dual-camera plans more efficient than single-camera plans with an extra camera "tagging along"?

Optimize:
Single Camera

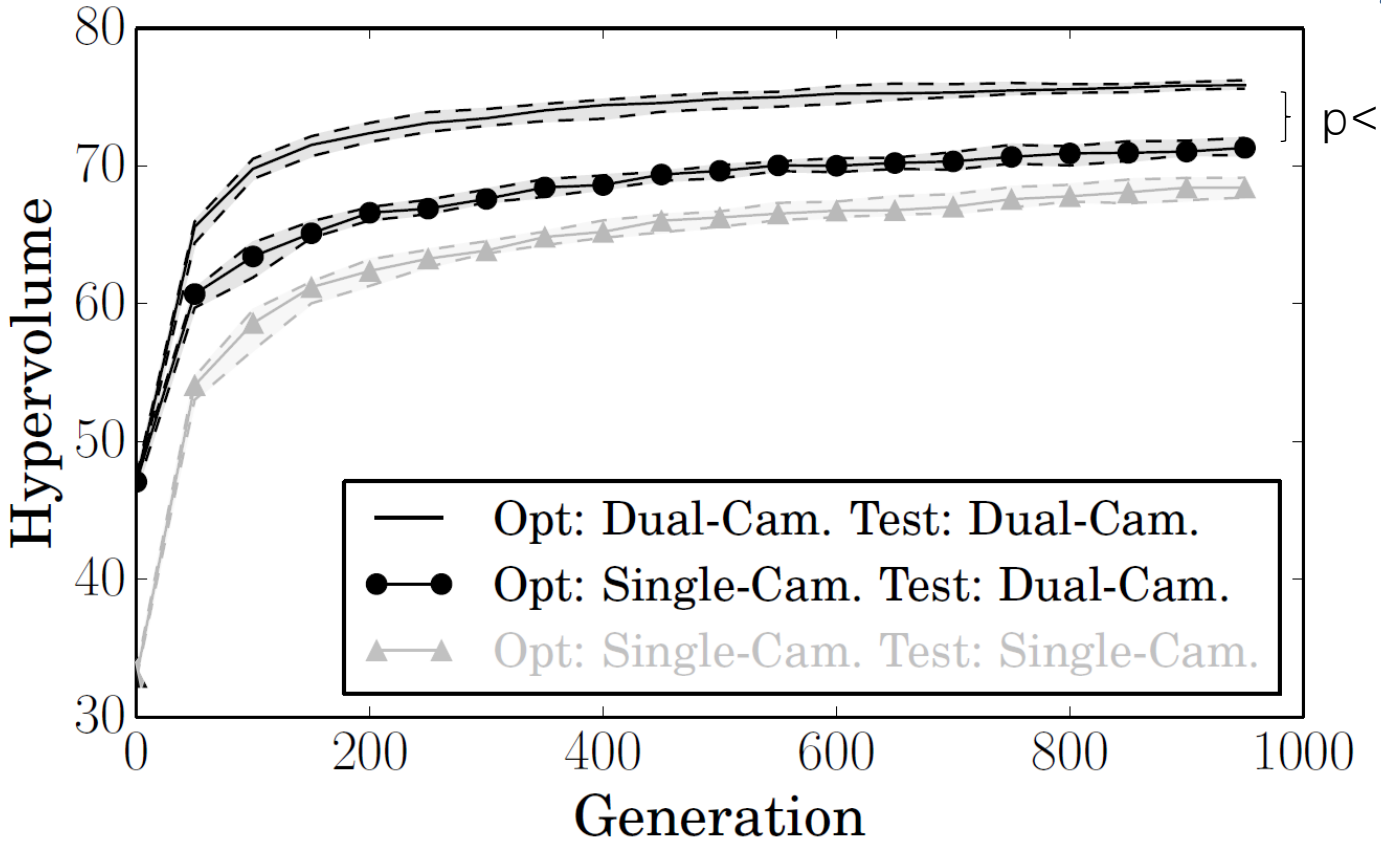
Optimize:
Dual Camera

Post-optimization
Test:
Dual Camera

Dual-Camera Inspection



Are the dual-camera plans more efficient than single-camera plans with an extra camera "tagging along"?



p<0.01

Conclusion

