COMPUTER SCIENCE
UNIVERSITY OF MARYLAND

NEMO: Autotuning power and performance

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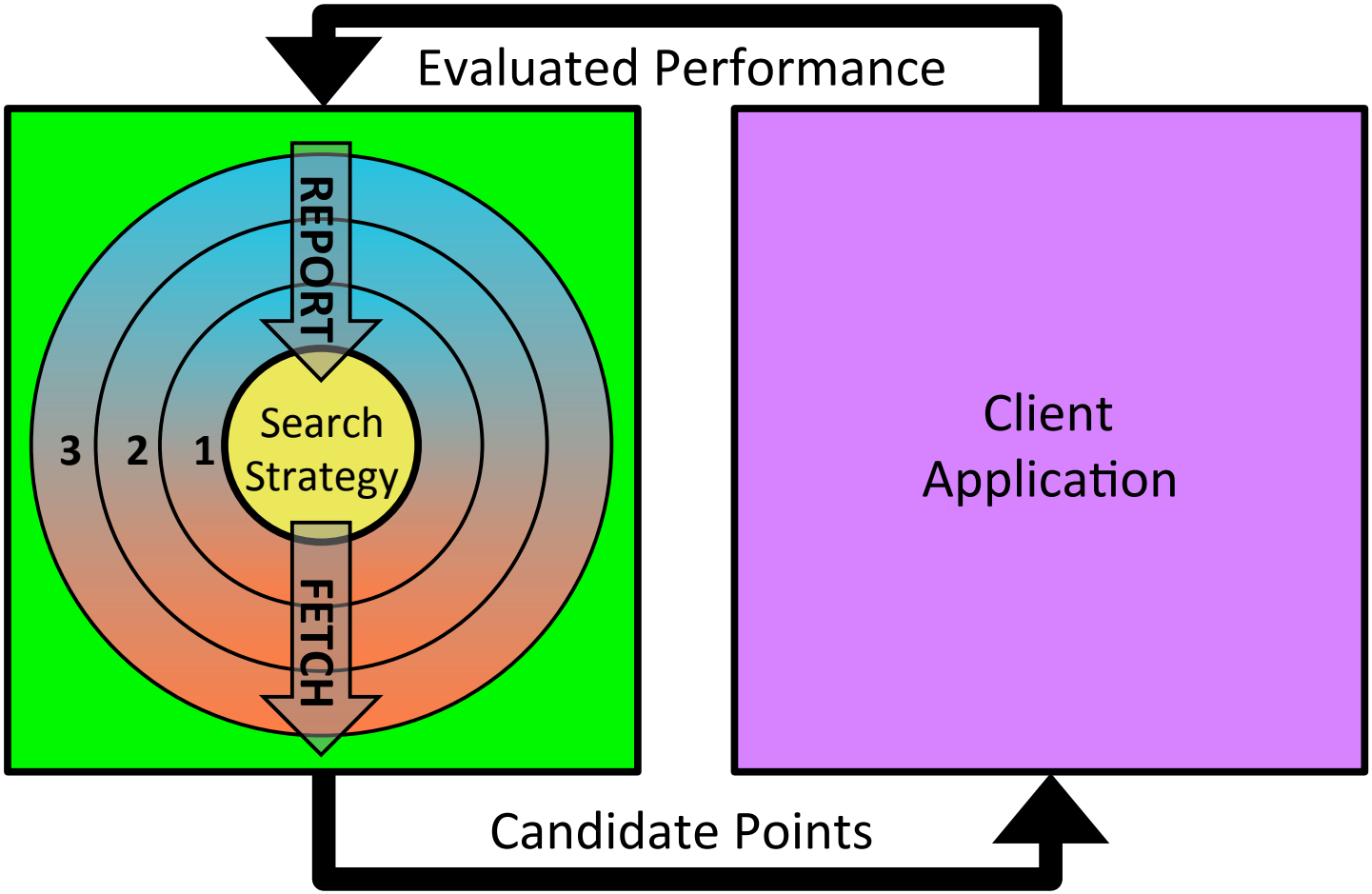
A Word About Power

- What can you do with 14MW?
  - Make Snow for Snow Summit (13.6 MW)
  - There are > 400 ski resorts in the US
- What can you do with 75 MW?
  - Make steel (60-90MW is typical)
  - 8 such mills in Malaysia
- Does that mean exascale is more useful than a ski resort and less than a steel mill?

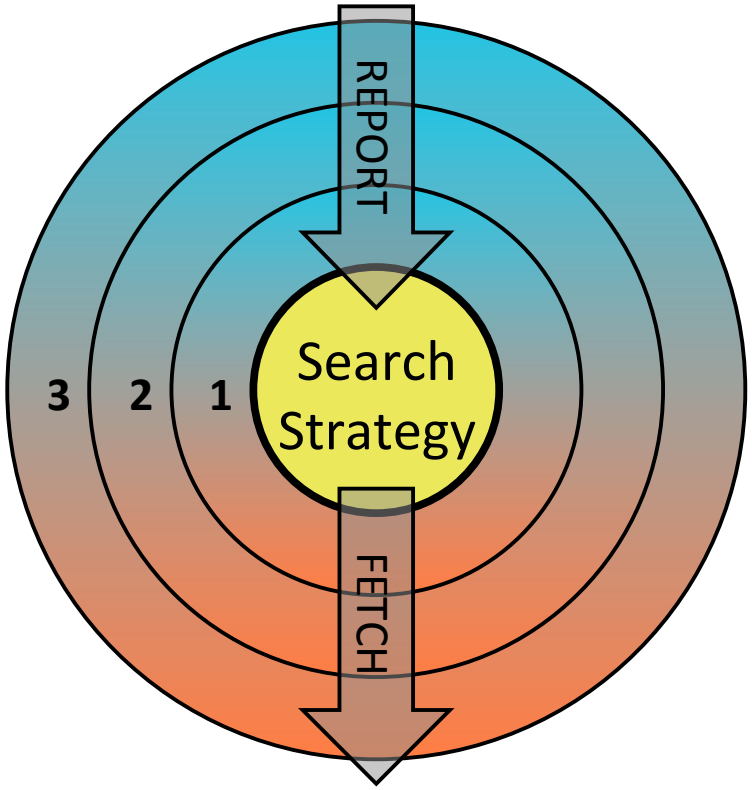
One more Thought on Power

- US has spent $100M on exascale to date
  - Perhaps for little/no return
- Could have purchased 20MW for 5 years
  - So a 40 MW machine could have worked
- In the future power may really matter, but
  - Let mobile market solve that for us
  - Let the Search/booksellers experts work on power
    - We could then work on the science & impact exascale can have to society

Generalized Auto-Tuning



Onion Model Workflow



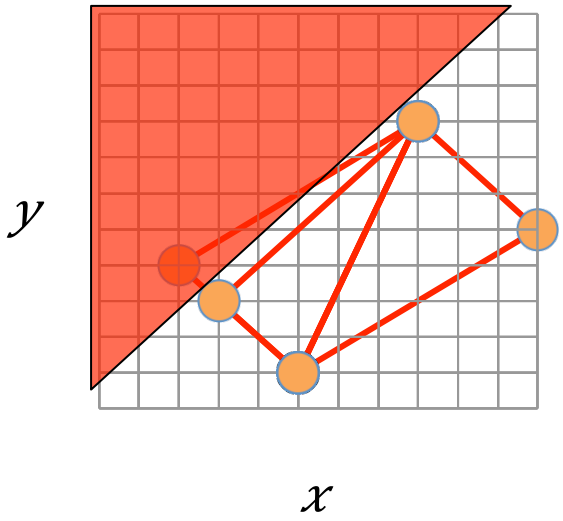
- Allows for paired functionality, but either hook is optional.
- Fetch hooks executed in ascending order.
- Report hooks executed in descending order.
- Point values cannot be modified (directly).

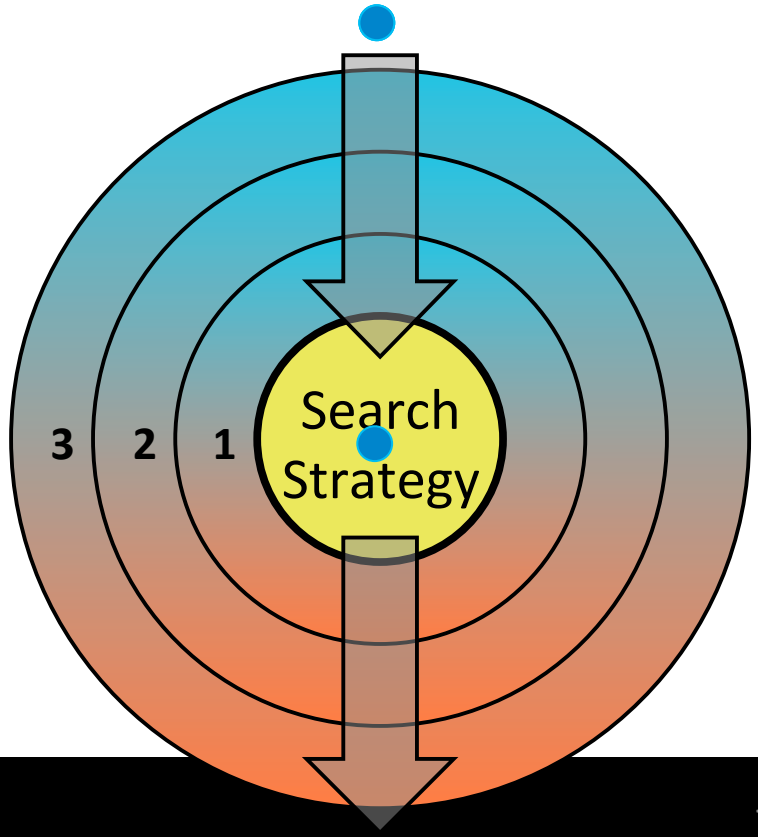
Search Strategies

- Allow for new algorithms to be tried
- All other plugins still work
- Current Search Strategies
  - Exhaustive
  - Parallel Rank Order
  - Nelder-Mead

Plug-in Example: Constraints

- Support for non-rectangular parameter spaces.
  - Implemented as plug-in #2 using REJECT workflow.
  - $y \leq x$



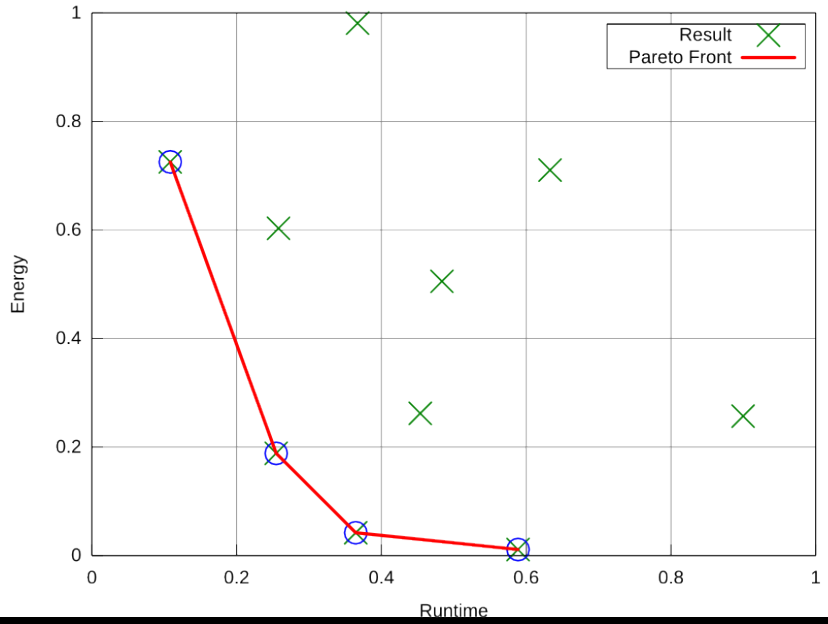


Auto-Tuning Objectives

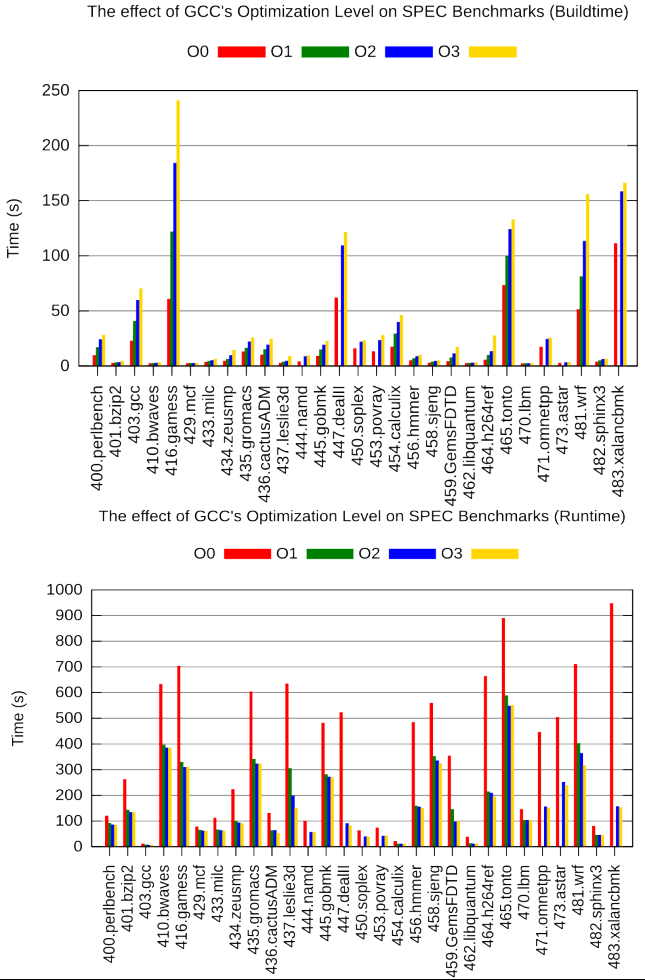
- Single Objective
  - "More apples is better."
  - The best solution is easy to select
- Multi-Objective
  - "Is more apples, or more oranges better?"
  - Multiple different, but equally good solutions
  - The best solution becomes a subjective choice

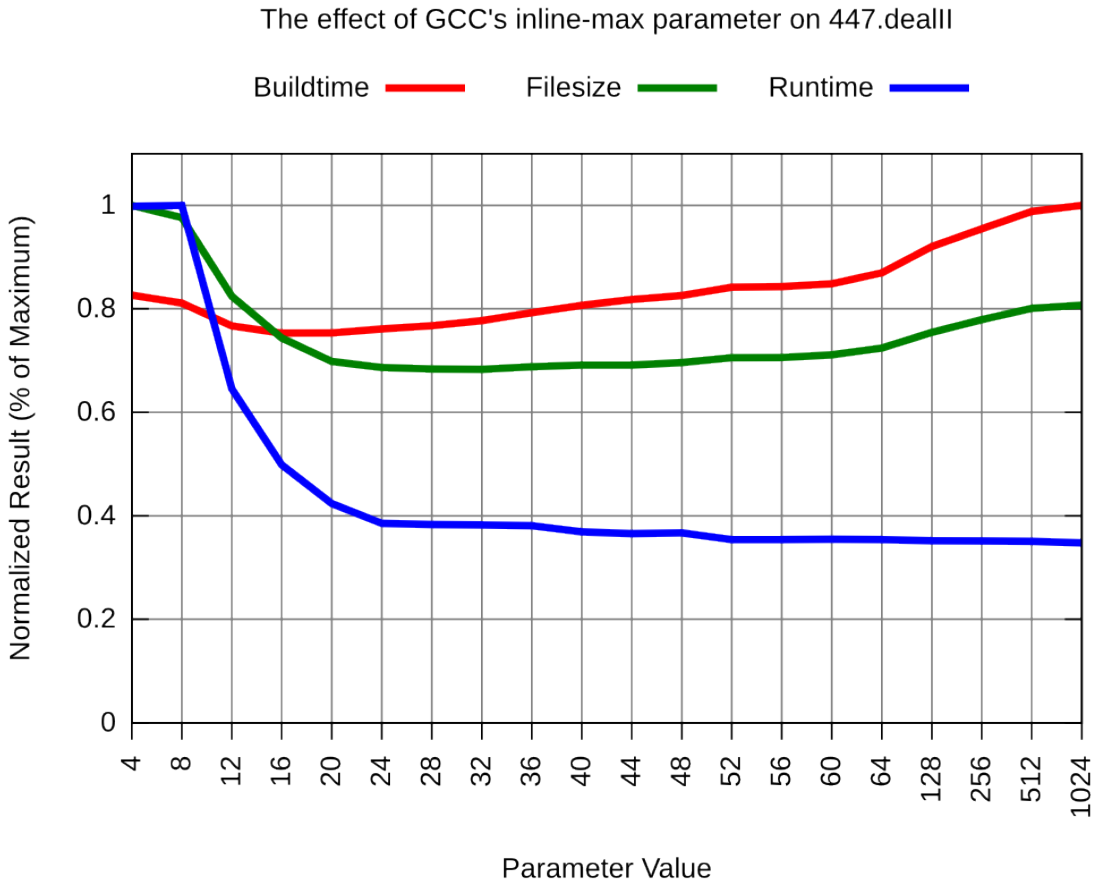
Multi-Objective Example

- Minimize both energy and runtime
- Pareto set formed by non-dominated solutions
  - Solutions cannot be strictly improved upon



Impact of Compiler Options





Existing Approaches

- Use experiments to find entire Pareto set
  - Algorithms judged by accuracy and efficiency
  - Evolutionary algorithms are widely used
- Provide set to users for final selection
  - This step is unacceptable for auto-tuning

Introducing NEMO

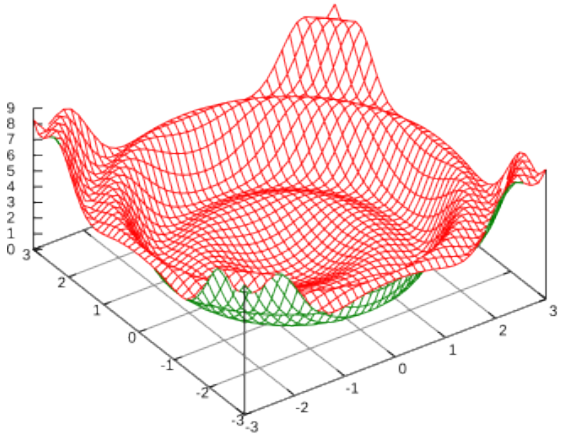
- Non-Evolutionary Multi-Objective Search Algorithm
- Goal:
  - Return a single solution, not a set of solutions
- Inputs:
  - Objective preference ranking
    - "When in conflict, I prefer runtime to be optimized over power."
  - Objective leeway percentage
    - "The search may stray up to 20% from the best known runtime."

NEMO Algorithm

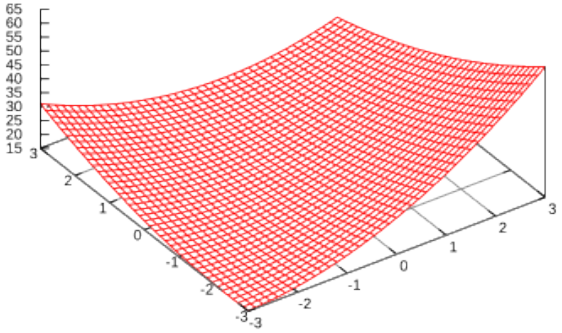
- Consider the first objective in isolation
  - Search using single objective search algorithm
  - Nelder Mead used in our experiments
- Record a threshold for first objective using leeway
  - Penalize any future searches that exceed threshold
- Repeat for objectives 2 through N
  - Search “landscape” changes with each iteration
  - Final landscape affected by all prior thresholds
    - Single objective search led to proper multi-objective solution

NEMO Example

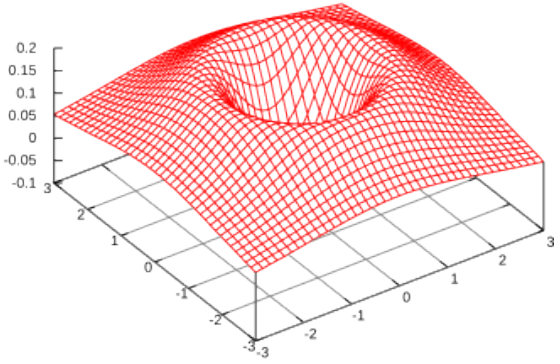
VLMOP3 Objective 1



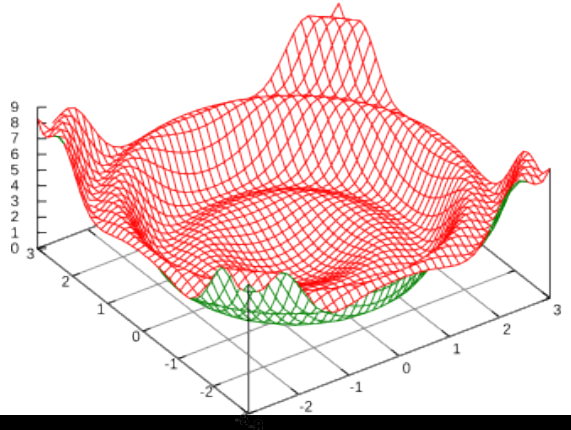
VLMOP3 Objective 2



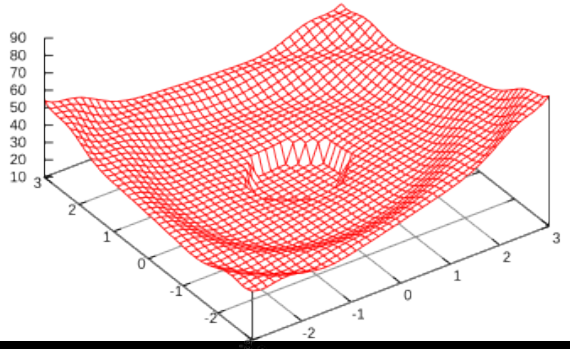
VLMOP3 Objective 3



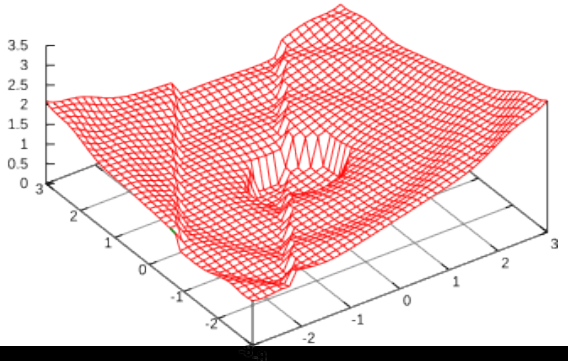
NEMO Search Phase 1
(No Thresholds Available)



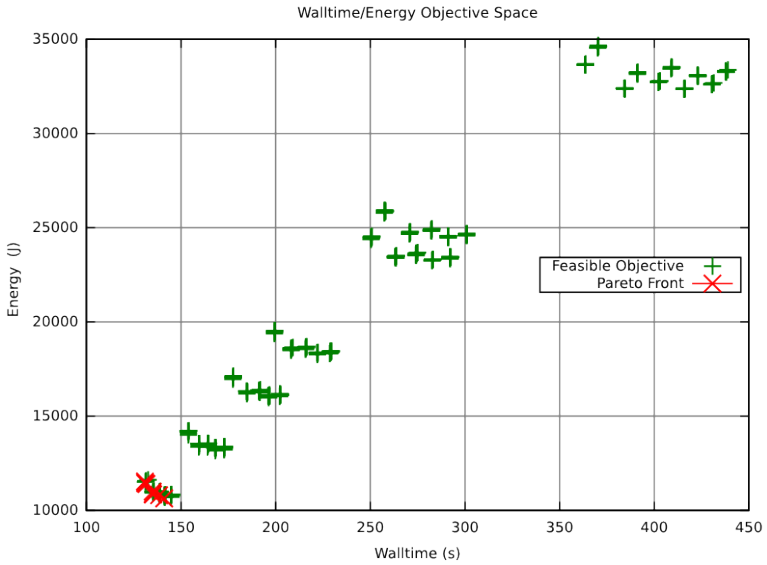
NEMO Search Phase 2
(Penalized for threshold violations
of Objective 1)

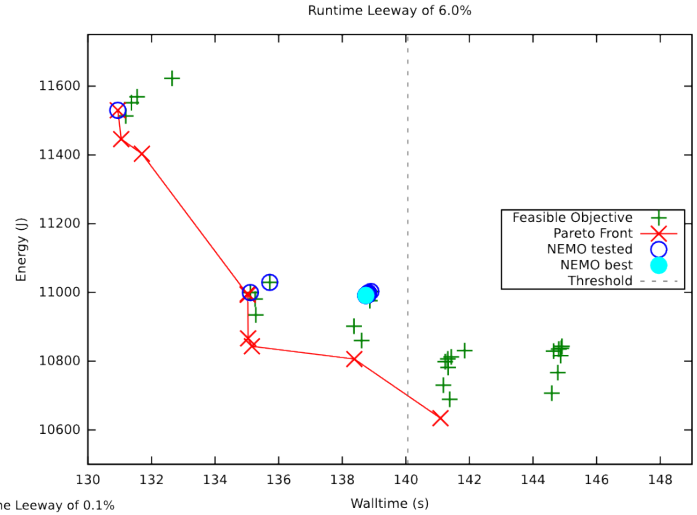


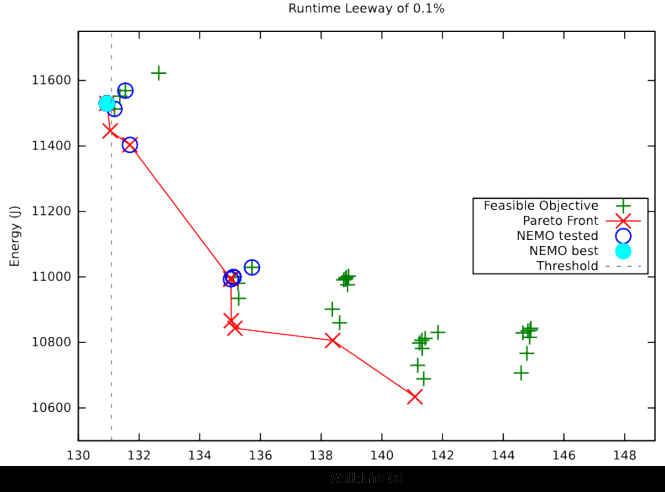
NEMO Search Phase 3
(Penalized for threshold violations
of Objective 1 & 2)



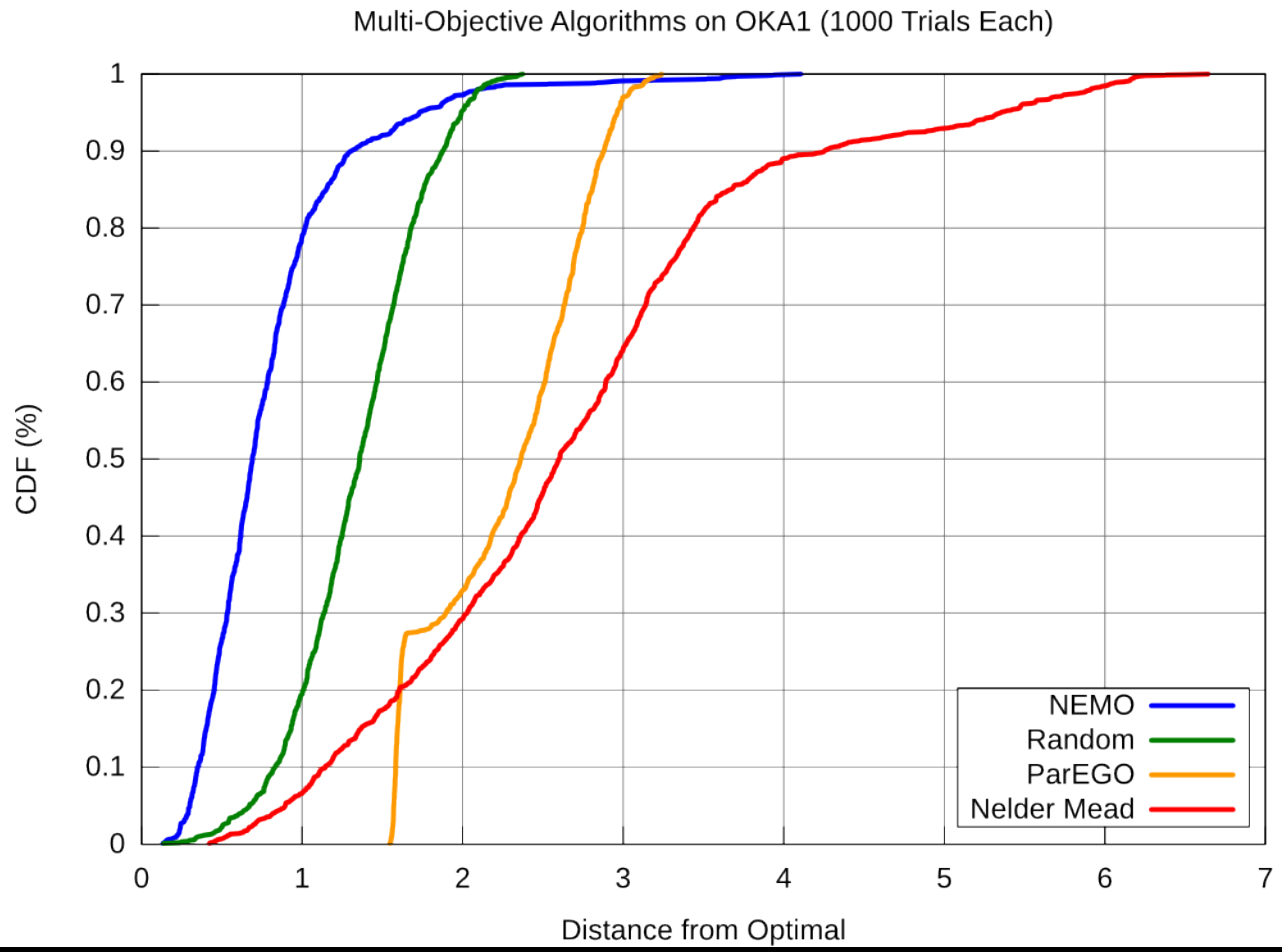
Tuning Lulesh







Preliminary Results



Conclusions

- Need to efficiently support multi-objective search
  - At least 2 objectives, likely more
  - NEMO is a promising option for this