Pareto-based Multi-Objective AI Planning

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DESCARWIN

Agenda

- Multi-Objective Optimization
- Multi-Objective AI Planning
- Divide-and-Evolve (DaE)
- Experiments
- Conclusions

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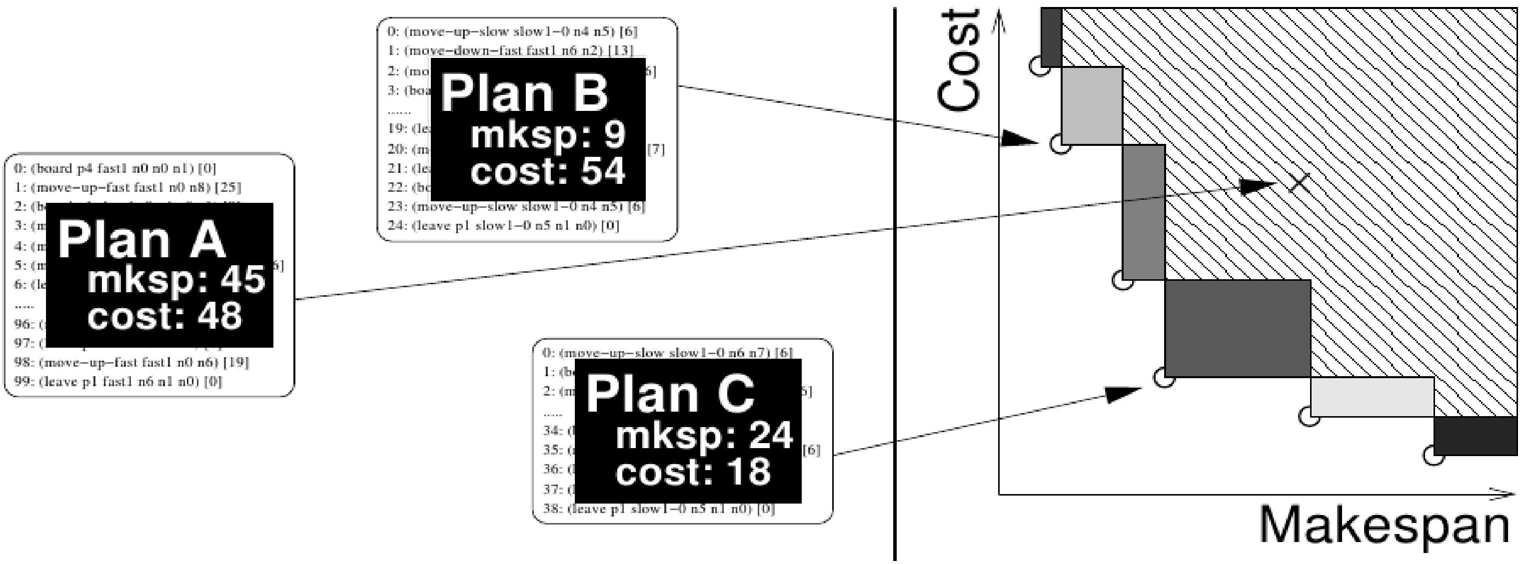
Multi-Objective Optimization

- Real-world problems are multi-objective:
  - Quality/cost, makespan/cost, ...
  - No single solution, but a set of trade-offs

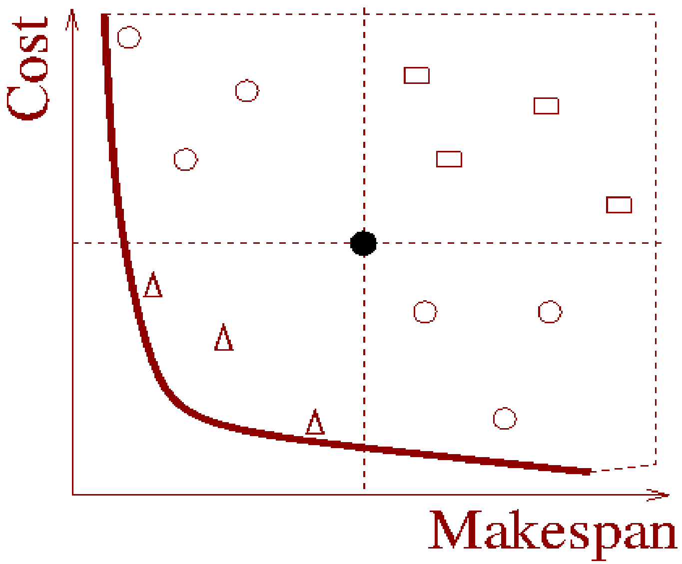


Design space: solution plans

Objective space: plan qualities

Multi-Objective Optimization

- Pareto-dominance:
  - A dominates B is A is better than B on all objectives

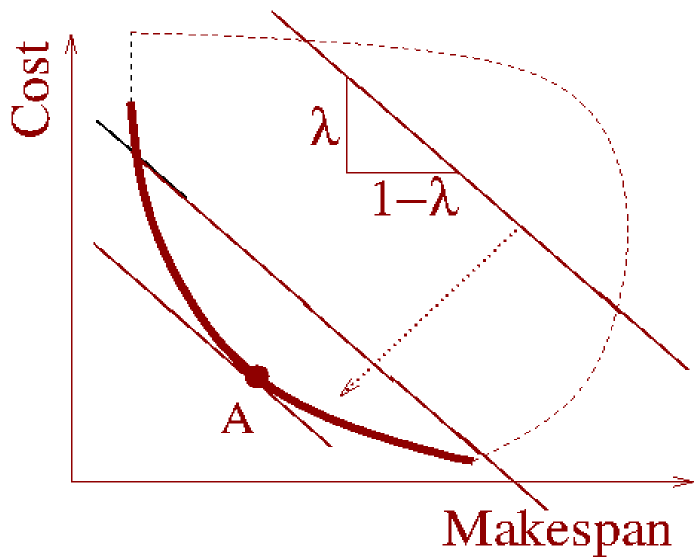


● dominates ⊡
is dominated by △
is not comparable
with ○

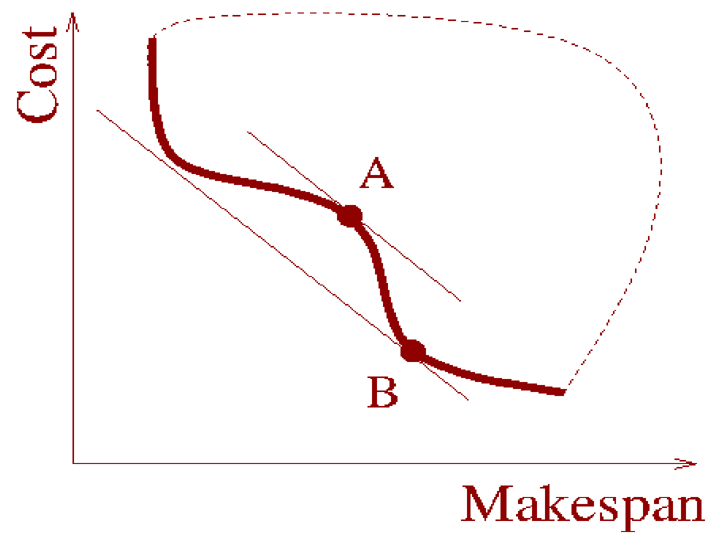
  - The set of non-dominated points in objective space is called Pareto front(ier)

Non-Pareto approaches

- Aggregation of objectives
  minimize λ makespan + $(1-\lambda)$ cost, $\lambda \in [0,1]$



→ single objective optimization

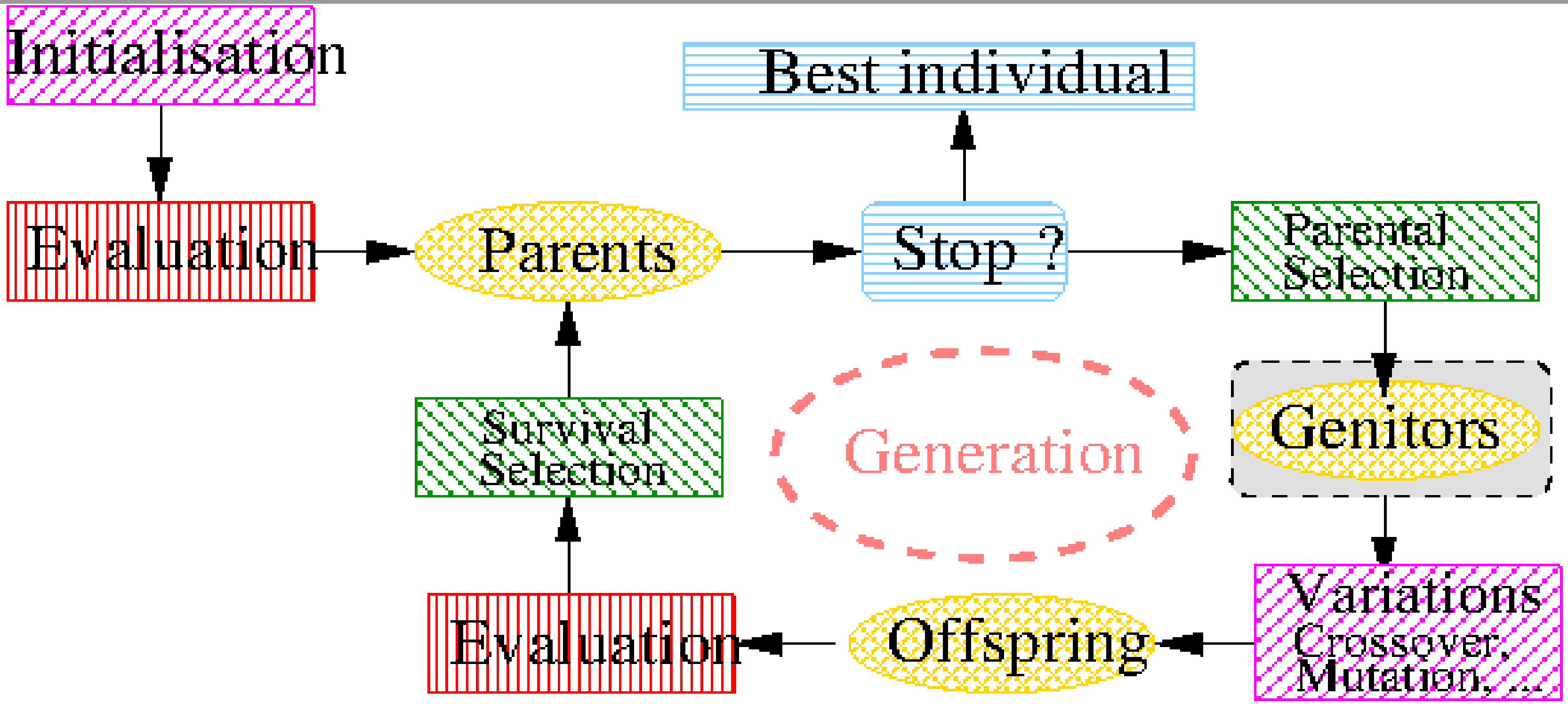


Fails on concave parts of Pareto Front

Evolutionary Algorithms

- Stochastic Optimization Algorithms
  - Population-based – distribution based
  - Very flexible
    - Any search space (with proper variation operators)
    - Any objective/constrts (very weak hypotheses)
  - Very costly
- Empirical successes
  - The second best method for any problem
  - The method of choice when everything else has failed
-

Evolutionary Algorithms



Stochastic operators Representation dependent

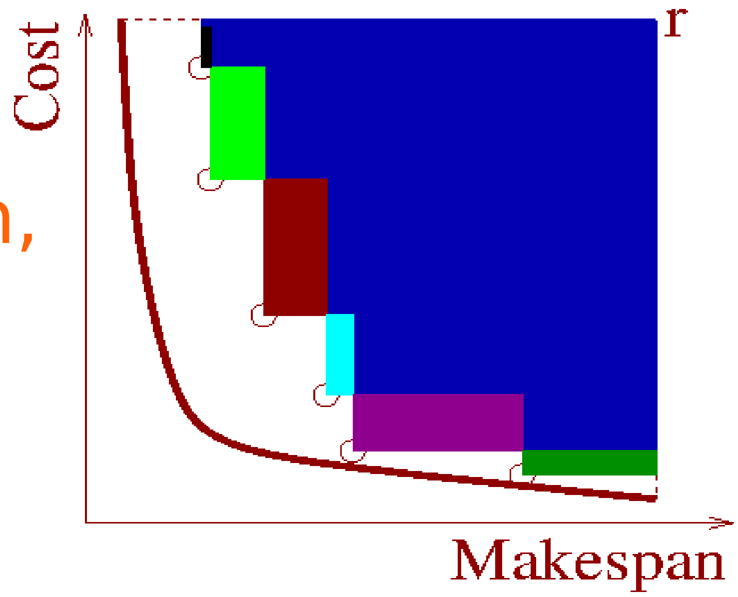
Darwinian Evolution Engine (can be stochastic or deterministic)

Main CPU cost

Checkpointing: stopping criterion, statistics, updates, ...

Evolutionary Multi-Objective Optimization

- Use Pareto-based selection
  - Pareto-ranking + diversity preserving e.g., NSGA2, SPEA2, ...
  - Hypervolume contribution, IBEAH [Zitzler & Künzli 2004],



- + archive all non-dominated points

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AI Planning & Benchmarks

- Biennal IPC (International Planning Competition)
  - Since 1998 (7th in 20...11)
  - Drive for PDDL design/improvements
  - Endless source of benchmarks

- Lots of exact or satisficing **single-objective** planners
- Either cost-based (purely sequential) or temporal (actions can be run in parallel)

Multi-objective AI Planning

- PDDL 3.0 (2006) allows for several objectives
- But existing strategies/heuristics are not Pareto-compliant
- → aggregation of objectives

- A multi-objective track in IPC 5 and IPC 6 … not in IPC 7
- + recent approach [Sroka & Long, STAIRS 2012] using LPG [Gerevini et al., AI 08]

MiniZeno Benchmark (best makespan 8)

- Domain: unique predicate at

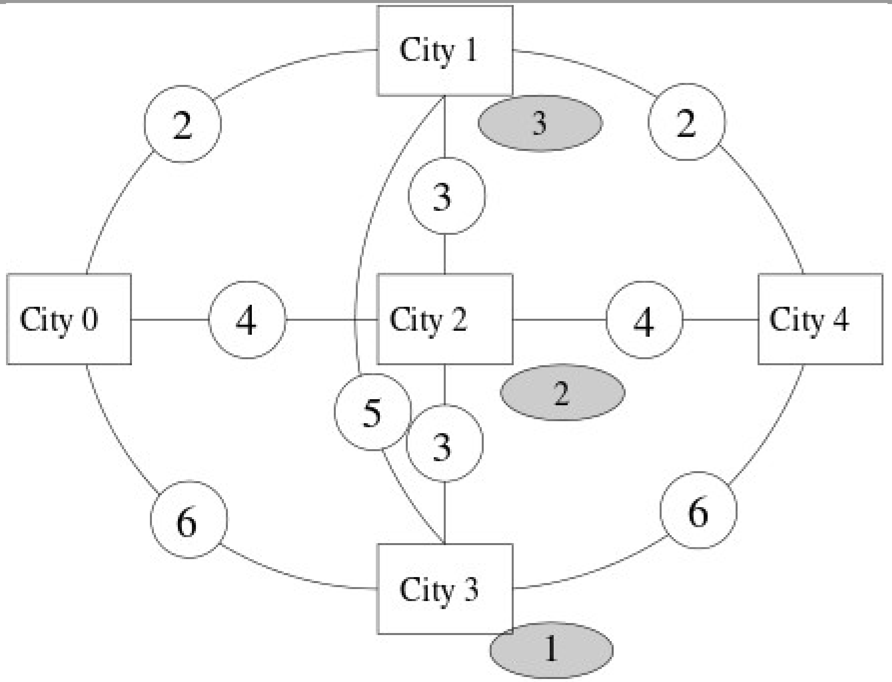
```
(:action fly  :duration (= ?duration (time ?c1 ?c2))
  :precond ((at ?a ?c1) (at ?p ?c1))
  :effect ((at ?a ?c2) (not(at ?a ?c1)) (at ?p ?c2) (not(at ?p ?c1))))
(:action flyVide  :duration (= ?duration (time ?c1 ?c2))
  :precond ((at ?a ?c1)) :effect ((at ?a ?c2) (not (at ?a ?c1))))
```

- Instance: 3 cities, 2 planes, 3 passengers

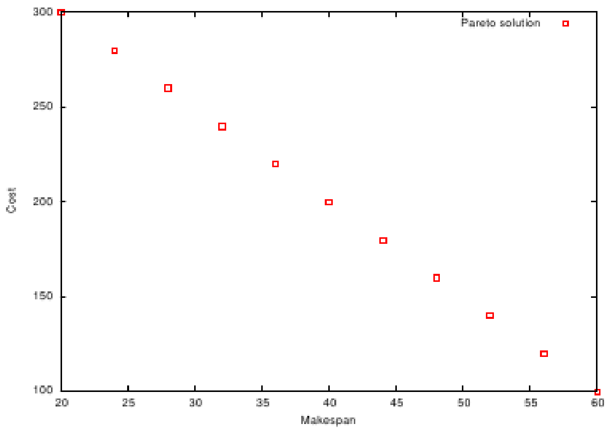
```
(:objects plane1 plane2, person1 person2 person3 city0 city1 city2)
(= (time city0 city1) 2)(= (time city1 city2) 2)
(= (time city1 city0) 2)(= (time city2 city1) 2)
(:init (at plane1 city0) (at plane2 city0) (at person1 city0)
  (at person2 city0) (at person3 city0))
(:goal (at person1 city2) (at person2 city2) (at person3 city2))
```

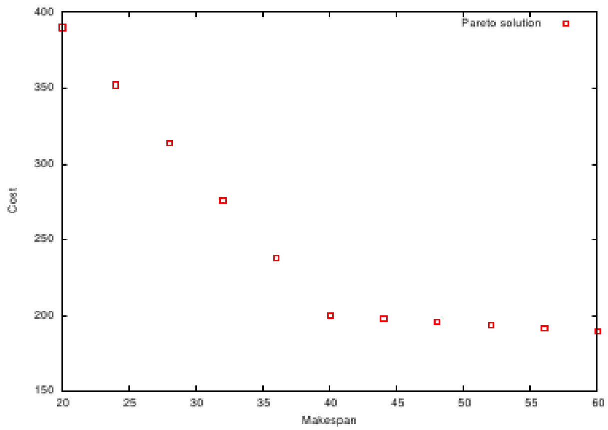
Multi-Objective MiniZeno Benchmark

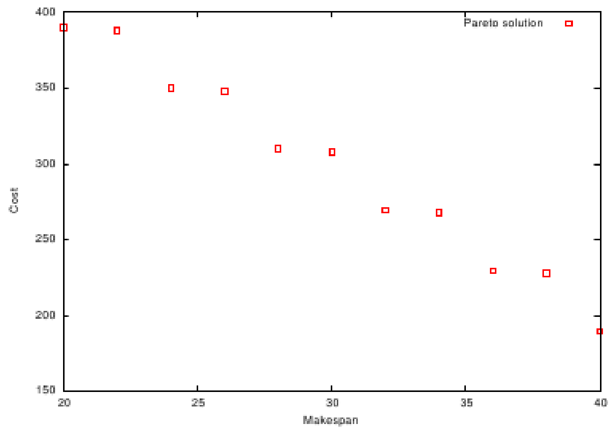
- 2 planes to bring 3 persons
- from city0 to city 4
- Two problems
  - Cost: additive
    (tax at every landing)
  - Risk: max
    (only highest value matters)



Pareto fronts for 6 passengers and varying cost/durations values







Multi-objectivization of IPC7 benchmarks

- From sequential satisficing and temporal satisficing tracks at IPC7
  - Merge identical instances of same domains if makespan and cost are contradictory (**`Elevators`**)
  - Set cost = Cst – makespan if not (**`CrewPlanning, FloorTile, ParcPrinter`**)
  - Add single cost action to temporal domain (**`OpenStacks`**)
-

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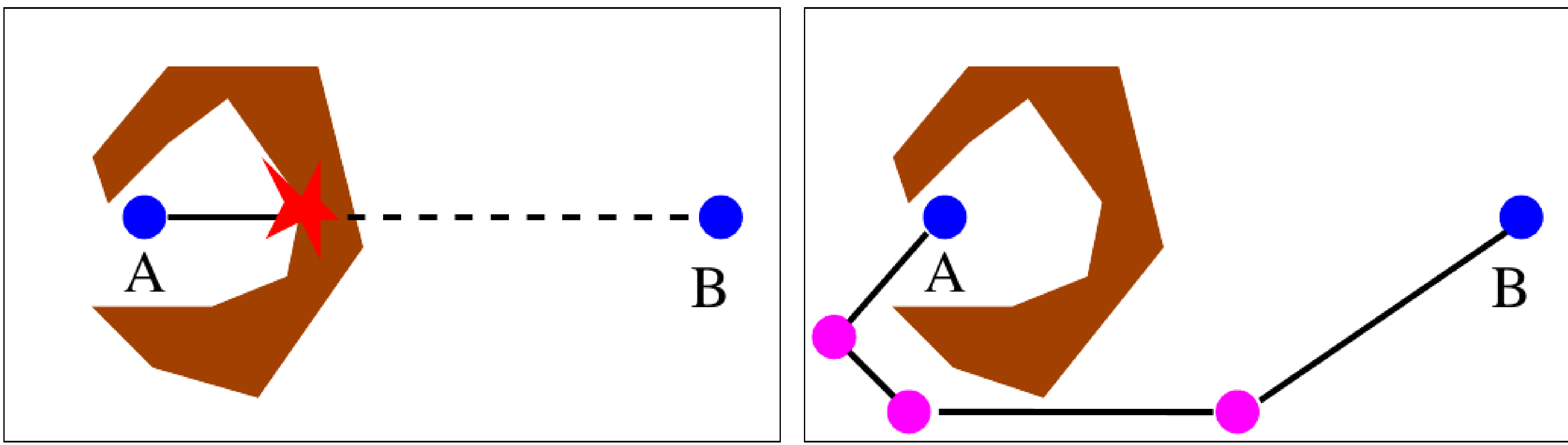
DaE: the Paradigm

- Slicing the original problem into a series of (hopefully simpler) sub-problems
- Using a 'dumb' solver on each sub-problem



(Variable length) Genotype = $(\bullet_1, \bullet_2, \bullet_3)$

DaE-YAHSP

Problem

$<S, A, I, G> = P_{D(I,G)}$

Representation

Ordered list of (partial) states $S_0 = I, S_1, \ldots, S_n, S_{n+1} = G$

Evaluation

Solve consecutive sub-problems $P_D(S_k, S_{k+1}) / k \in [0,n]$

with embedded single-objective planner YAHSP [Vidal, ICAPS 04]

Fitness

All problems solved: concatenate partial plans

Fails solving $P_D(S_l, S_{l+1})$: Penalization

Crossover: One-point crossover

Mutations : AddGoal, delGoal, addAtom, delAtom

Single-objective DAE-YAHSP

- An original (intricate) memetization strategy
- A very noisy fitness

but

- YAHSP is both cost- and temporal planner
- DAE-YAHSP: state-of-the-art performance in both domains [Bibai et al., ICAPS 2010]
- Silver medal, Humies Awards 2010
- Ranked 1st, temporal satisficing, IPC 2011

Multi-objective DAE-YAHSP

- YAHSP is both cost- and temporal planner

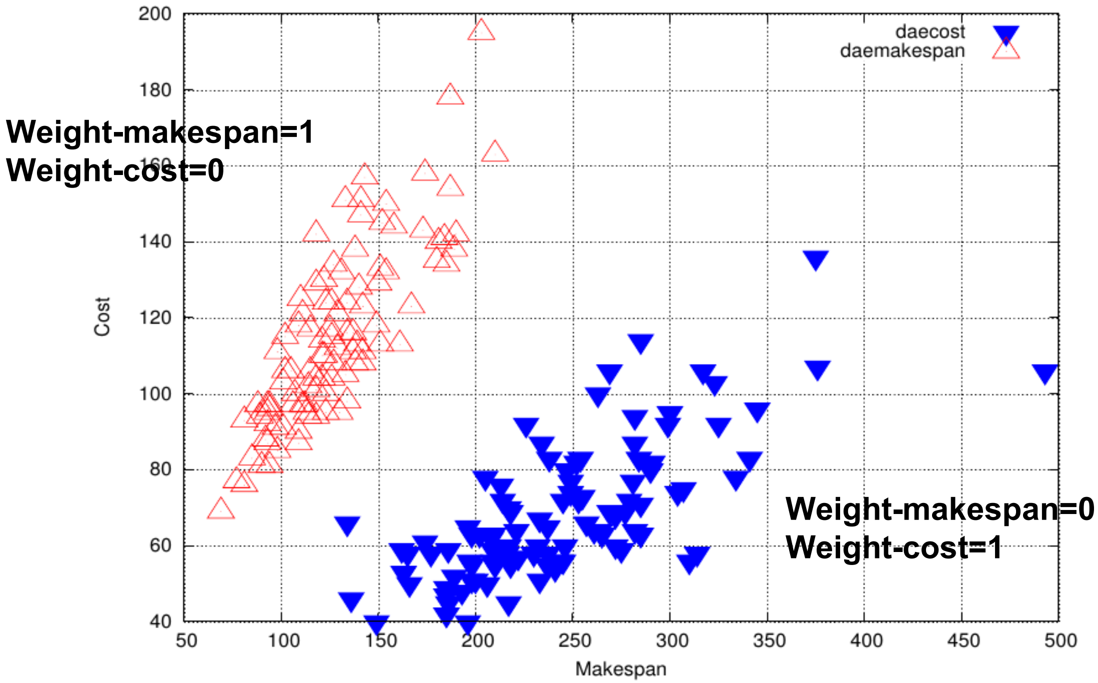
  … can compute one while optimizing the other
- « Only » need to change the EC engine !

  [Schoenauer, Saveant, Vidal, EvoCOP'06]
- Two possible strategies for YAHSP:

  Optimize makespan **or** cost/risk

YAHSP strategy

- Optimize cost or makespan?



Noisy fitness : objectives of a single individual computed by YAHSP with both pure strategies

→ randomize, and use weights (individual level)

Contributions

- The MiniZeno benchmark suite [EMO'13]
  - And the multi-objecvivization of some IPC7 problems
- IBEA best MO engine for MO-DAE [EMO'13]
- Parameter tuning: which fitness measure for the λ-runs? [LION'13]
- Comparison with aggregated approaches :
  - AGG-DAE [EvoCOP'13]
  - LPG [IJCAI'13]

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Aggregated Approaches

- Metric-sensitive planners directly optimize

  λ makespan + $(1-\lambda)$ cost, $\lambda \in [0,1]$

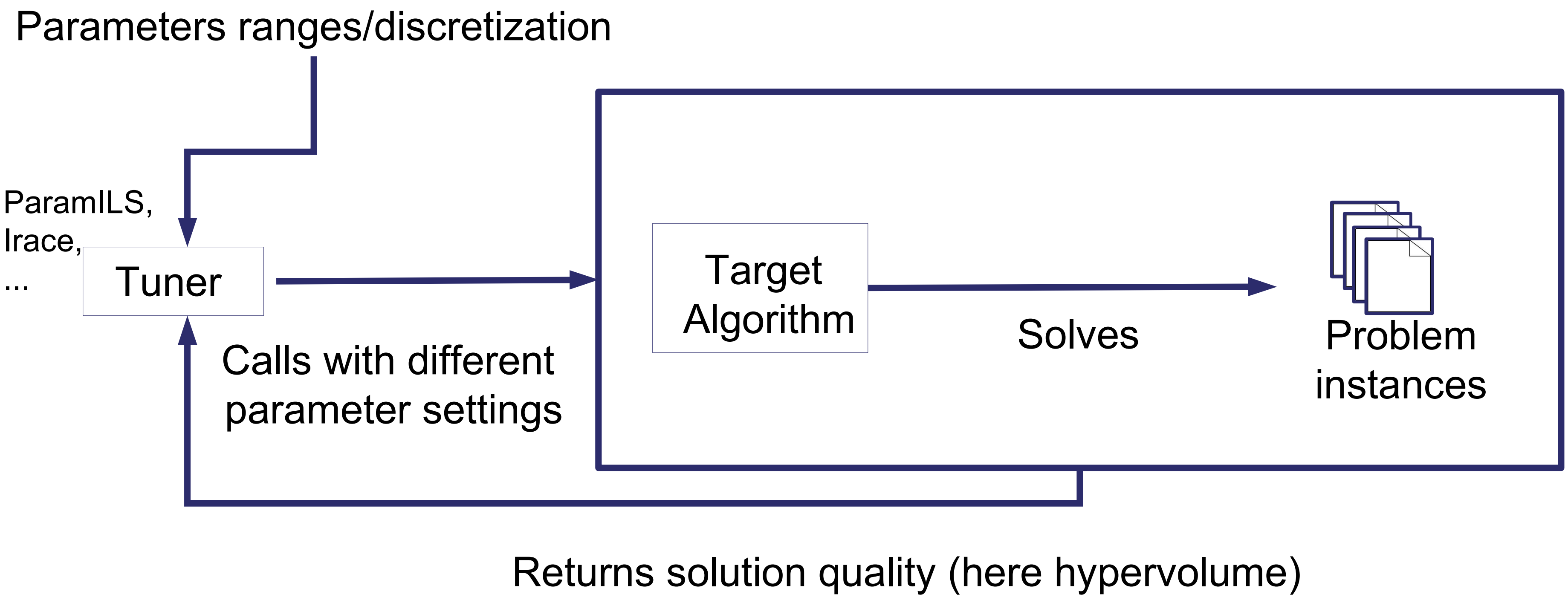
  – E.g. LPG [Gerevini et al., AI'08]
- YAHSP is not metric sensitive
  – but DAE is agnostic
- Repeated calls with different values of λ to approximate the whole Pareto front

→ Comparison of MO-DAE with both AGG-DAE and LPG

Experimental Conditions

- EC engine IBEA-Hv [EMO'13]
- Aggregation $\lambda = \{0, 0.3, 0.5, 0.7, 1\}$
- Implementation ParadisEO, C++
- Instances
  - MiniZeno3, MiniZeno6, MiniZeno9
  - Multi-objectivization of IPC7 instances
- 11 independent runs (also for each λ)
- Stopping criterion
  - ParamILS 48h (zeno3 and 6), 72h (zeno9, IPC7)
  - Optimization 300, 600 and 900s

Off-line Parameter Tuning



UBC ParamILS [Hutter et al., JAIR 2009]

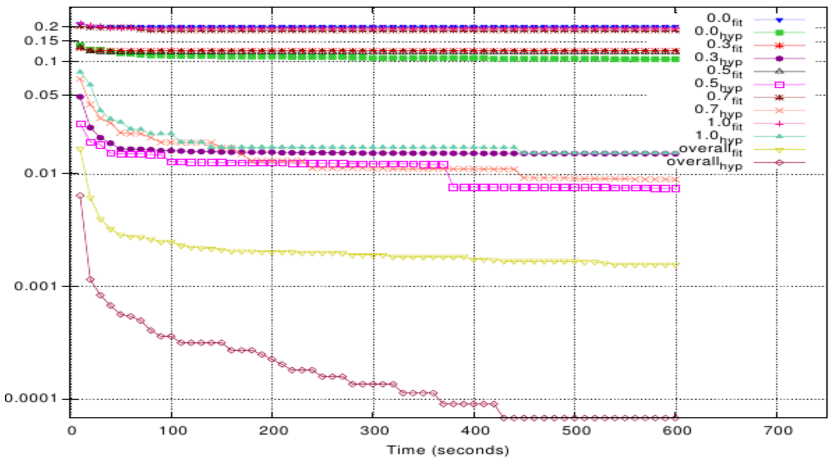
The Parameters

Parameters	Range	Description
W-makespan W-cost	0,1,2,3,4,5	Weighting for optimizing makespan during the search Weighting for optimizing cost during the search
Pop-size	30,50,100,200,300	Population Size
Proba-cross Proba-mut	0.0,0.1,0.2,0.5,0.8,1.0	Probability (at population level) to apply crossover Probability (at population level) to apply one mutation
w-addAtom w-addGoal w-delAtom w-delGoal	0,1,3,5,7,10	Relative weight of the addAtom mutation Relative weight of the addGoal mutation Relative weight of the delAtom mutation Relative weight of the delGoal mutation
Proba-change Proba-delatom	0.0,0.1,0.2,0.5,0.8,1.0	Probability to change an atom in addAtom mutation Average probability to delete an atom in delAtom mutation
Radius	1,3,5,7,10	Number of neighbour goals to consider in addGoal mutation

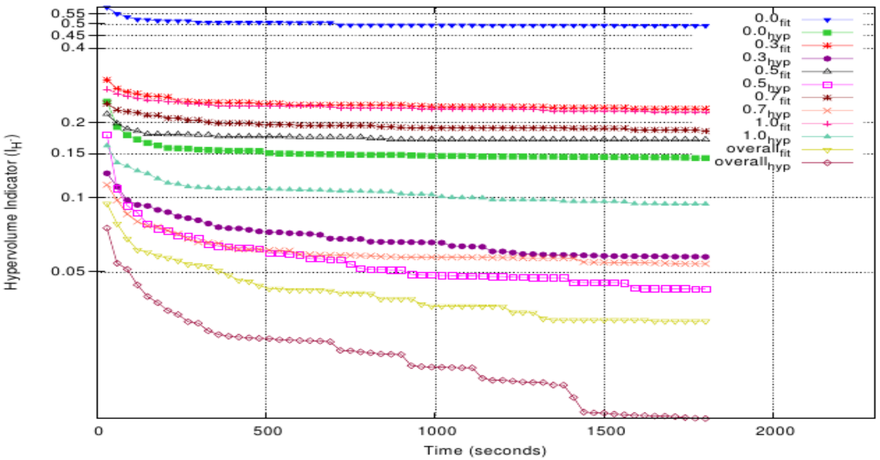
$\longrightarrow$ 1.5 * 10^9 Possible configurations

Metric for Parameter Tuning

- Hypervolume for MO runs
- Which metric for each of the λ-runs?
  - Hypervolume better choice than (aggregated) fitness [LION'13]

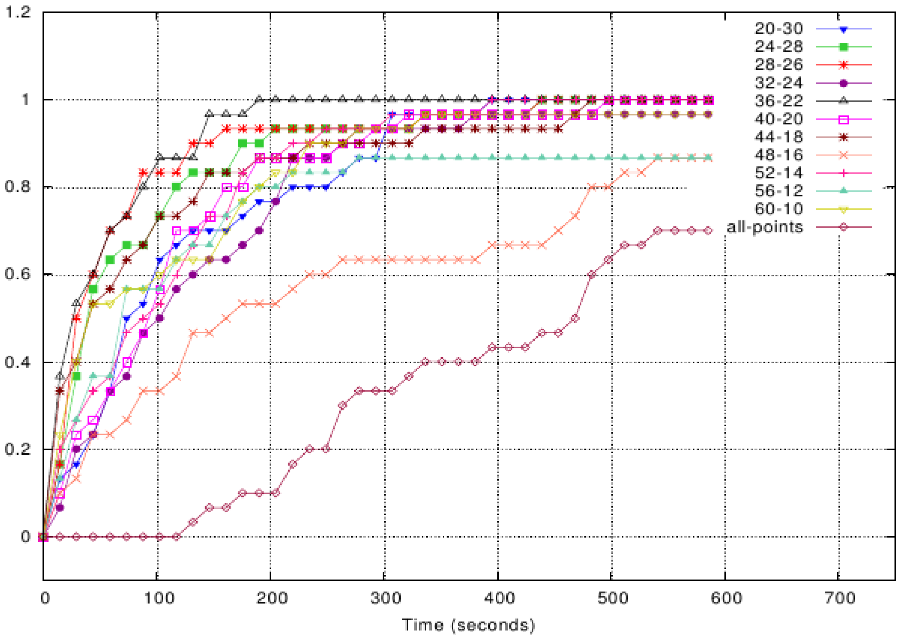


Zeno6

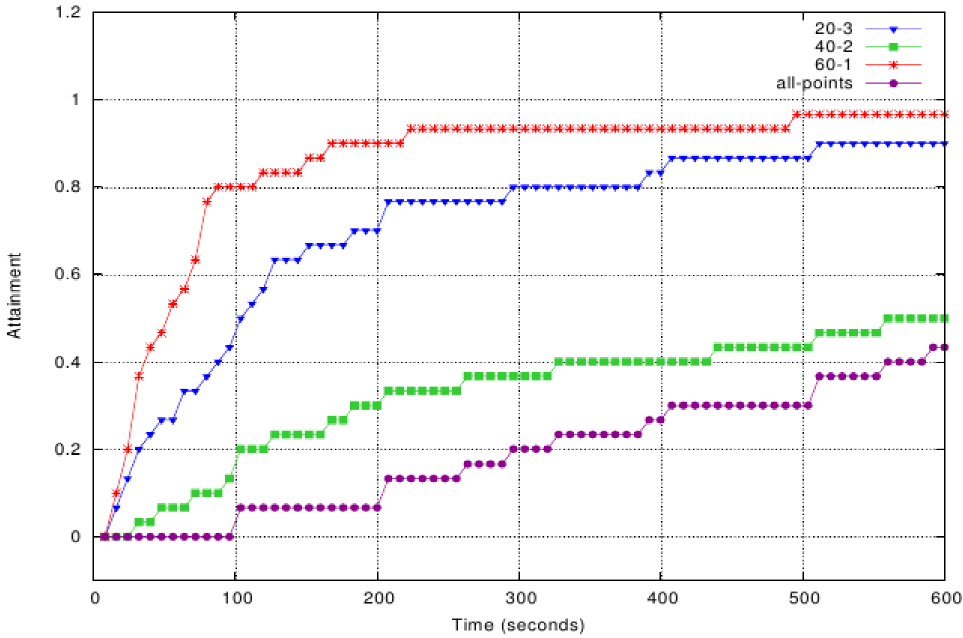


Zeno9

Pareto Front Attainability



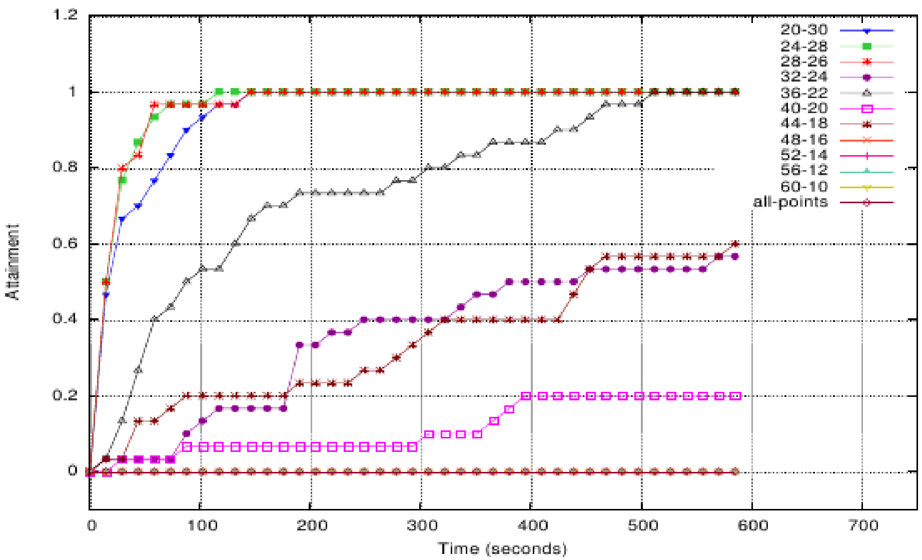
(a) MultiZeno6$_{cost}$



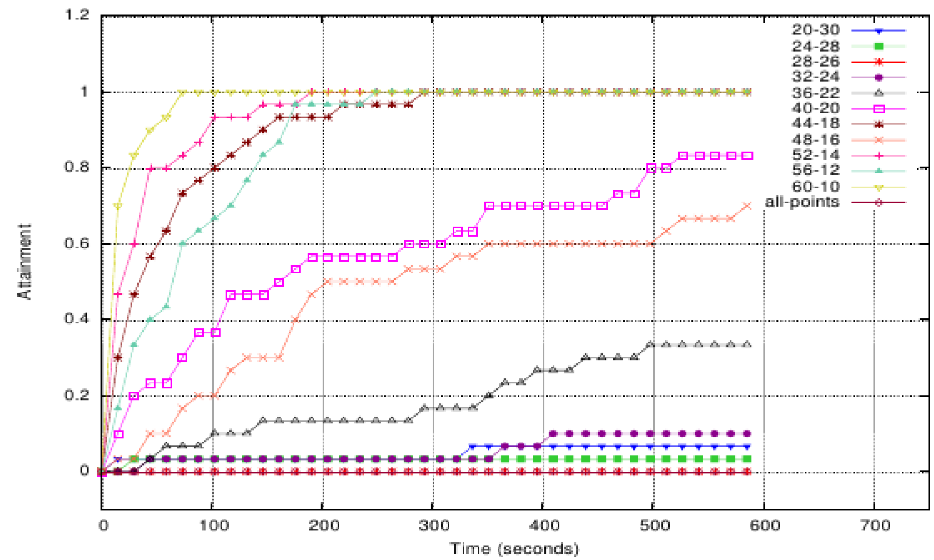
(b) MultiZeno6$_{risk}$

Hitting plots for Ibea-Hv on Zeno6 (Cost and Risk)

Influence of YAHSP strategy



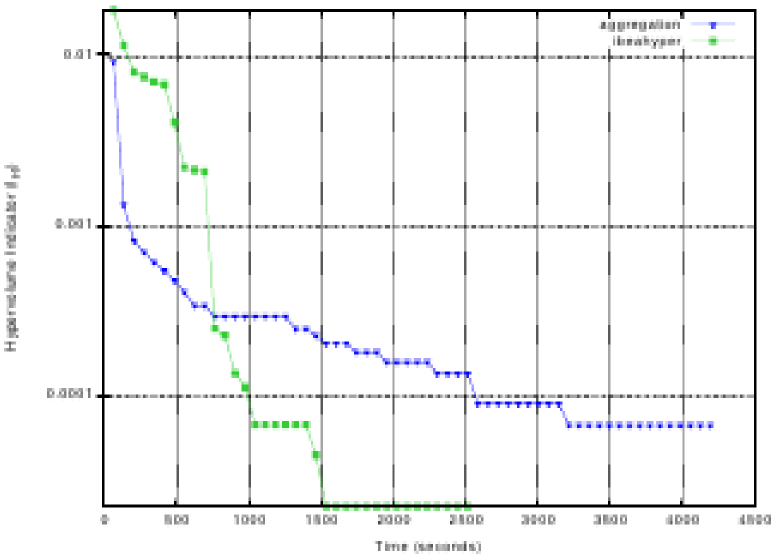
(a) YAHSP optimizes makespan



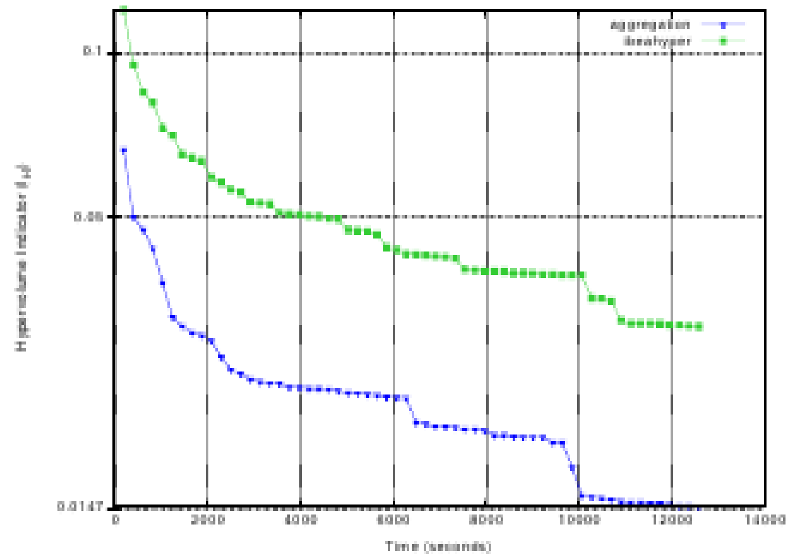
(b) YAHSP optimizes cost

Hitting plots for Ibea-Hv on Zeno6 for the 2 'pure' strategies

Pareto vs Aggregation - Cost



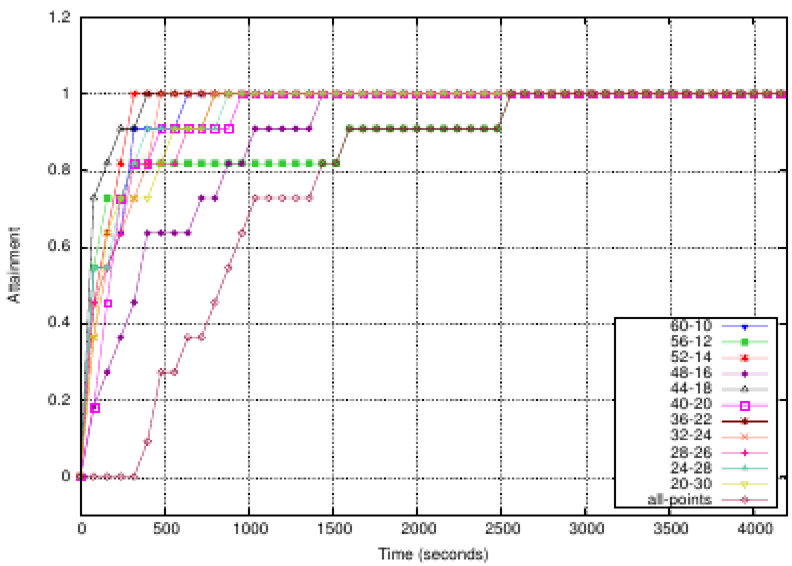
Zeno6



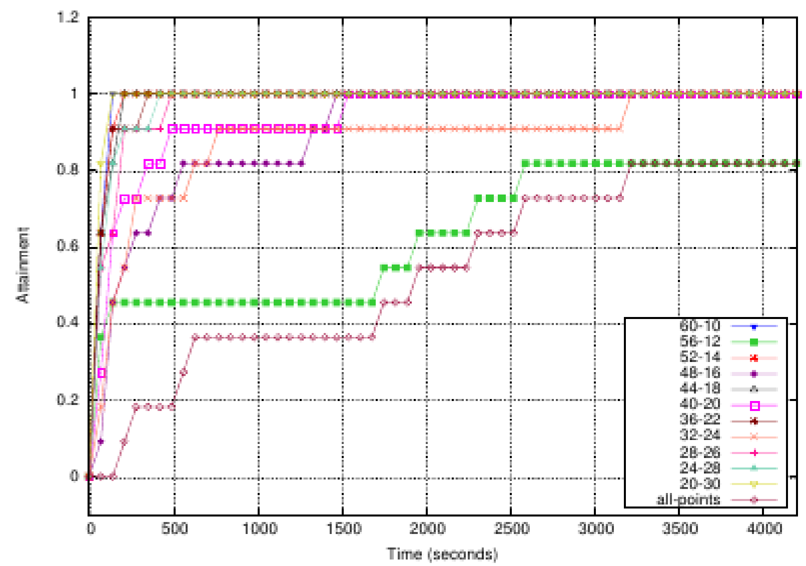
Zeno9

Hypervolume evolution for MO-DAE and AGG-DAE

Pareto vs Aggregation – Cost (2)



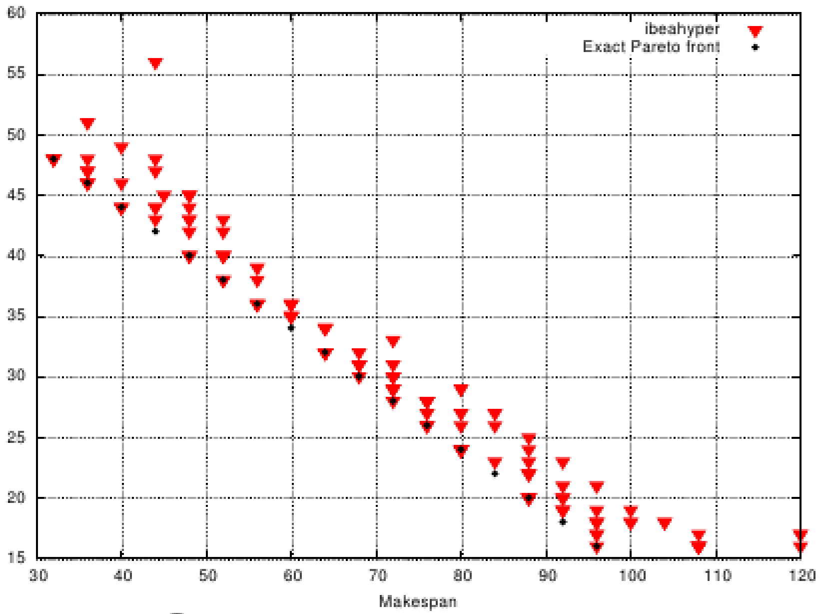
MO-DAE



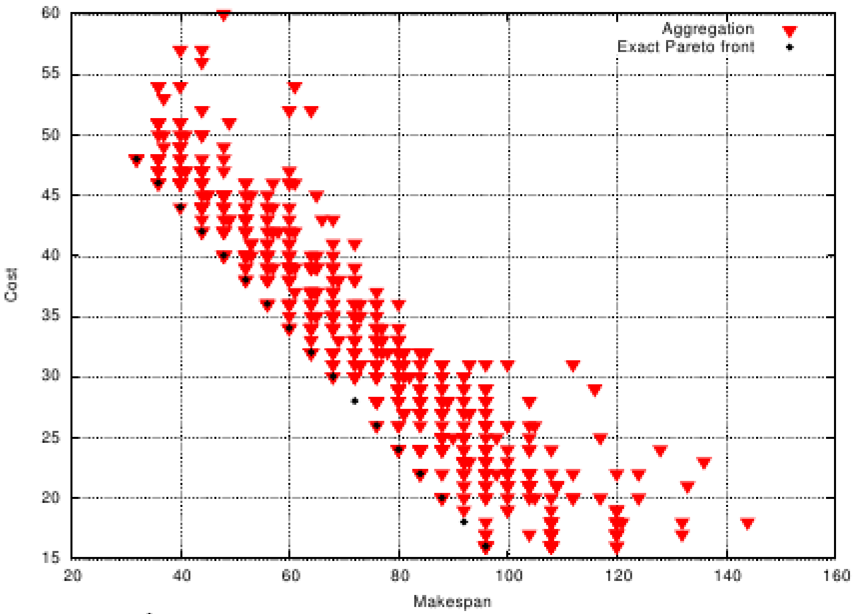
AGG-DAE

Hitting plots on Zeno6 for MO-DAE and AGG-DAE

Pareto Fronts for Zeno9-Cost



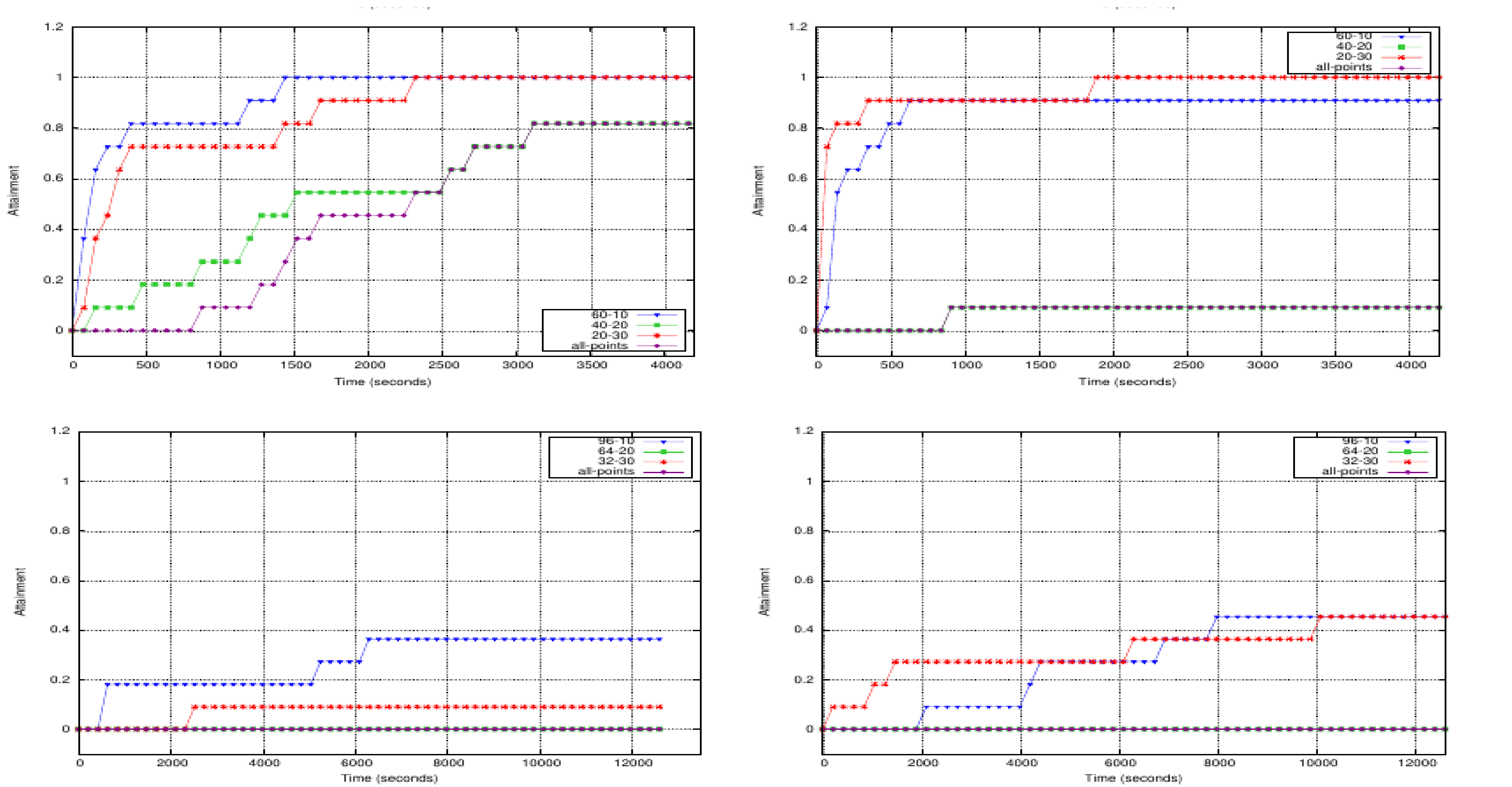
MO-DaE$_{\text{YAHSP}}$ on MultiZeno9



Agg-DaE$_{\text{YAHSP}}$ on MultiZeno9

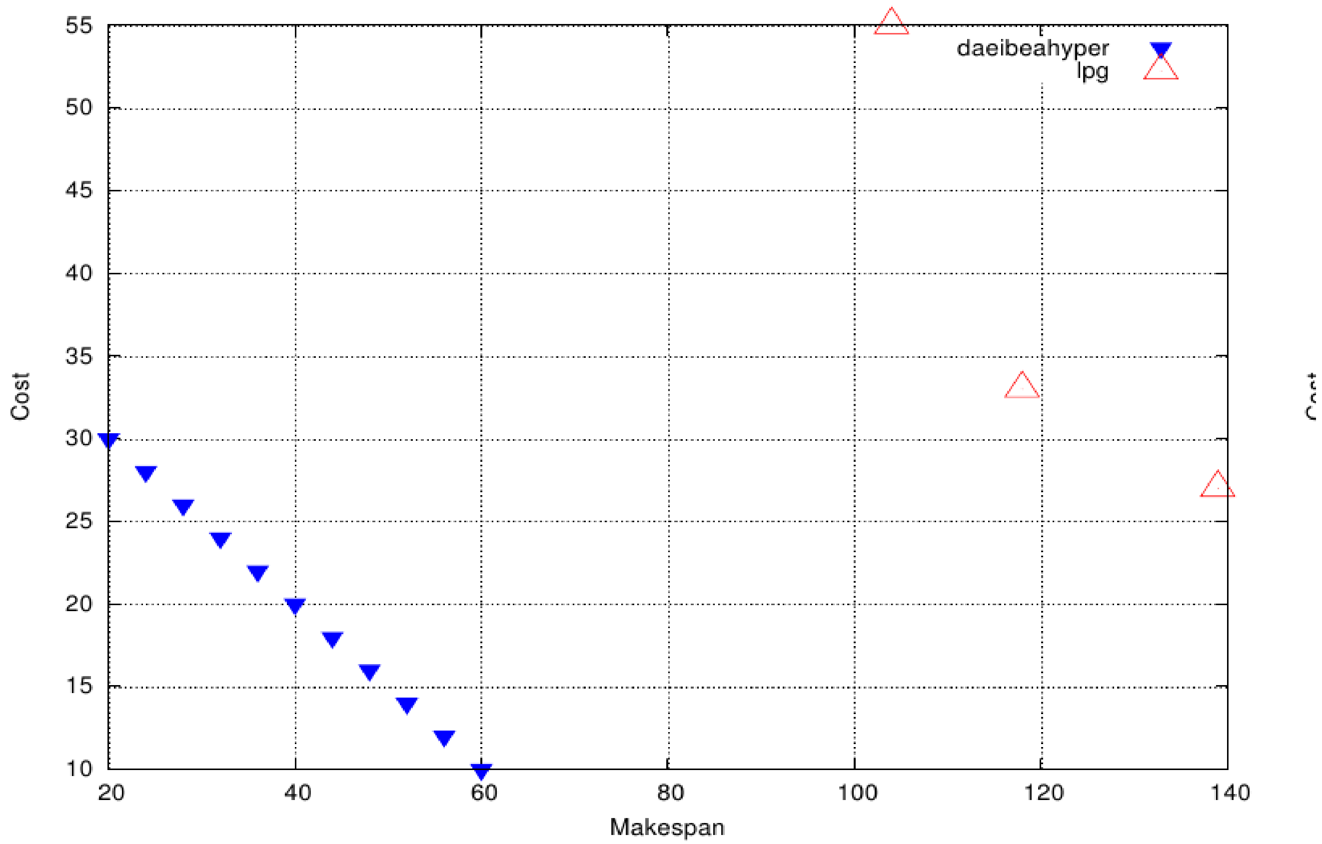
Pareto Fronts (from 11 runs) for Zeno9 (scales are different)

Hitting Plots for Zeno-Risk



MO-DAE (left) vs AGG-DAE (right) on Zeno6 (top) and Zeno9 (bottom)

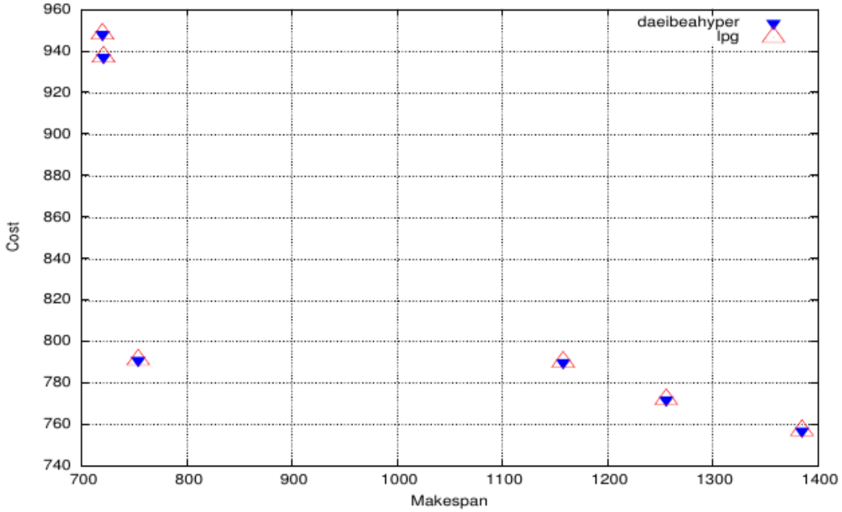
Comparison with LPG



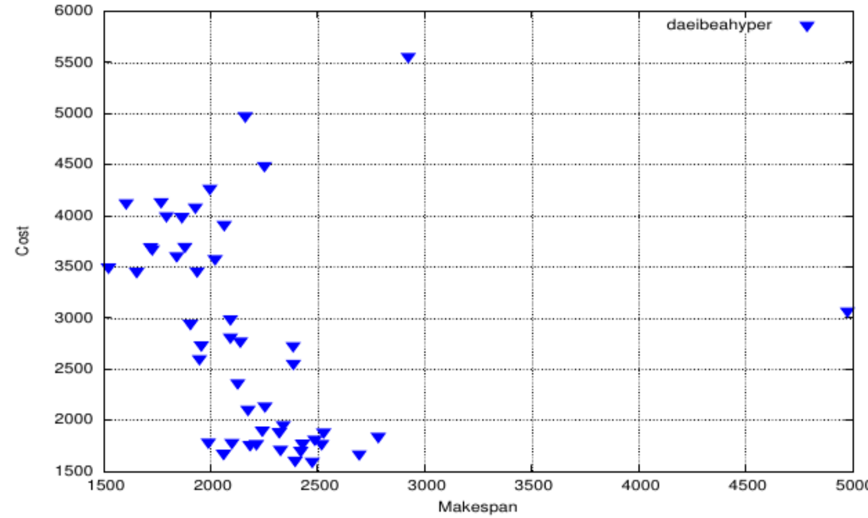
Pareto Fronts for MO-DAE and LPG on MiniZeno6

(LPG fails on MiniZeno9)

Comparison with LPG (2)



(a) ELEVATORS01:DAE (▼) vs LPG (△)



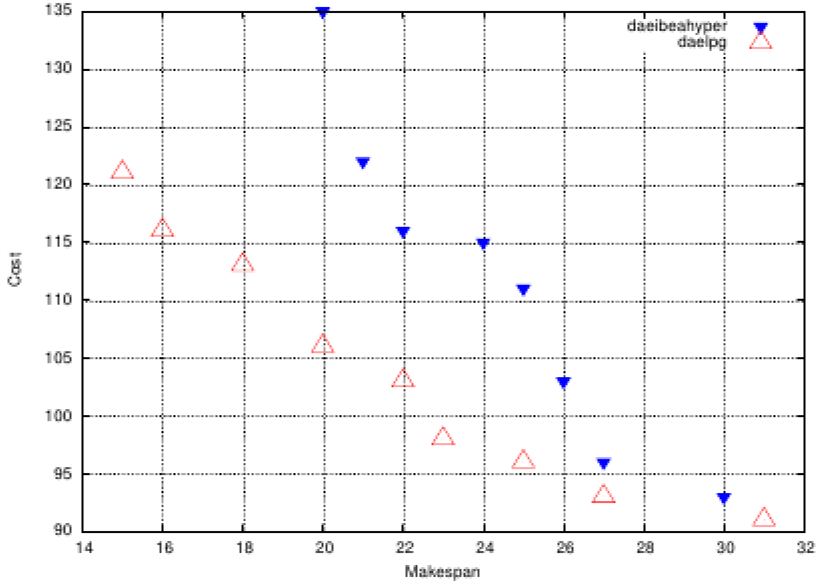
(d) ELEVATORS10: DAE

Identical Pareto Fronts for MO-DAE vs LPG on Elevators01

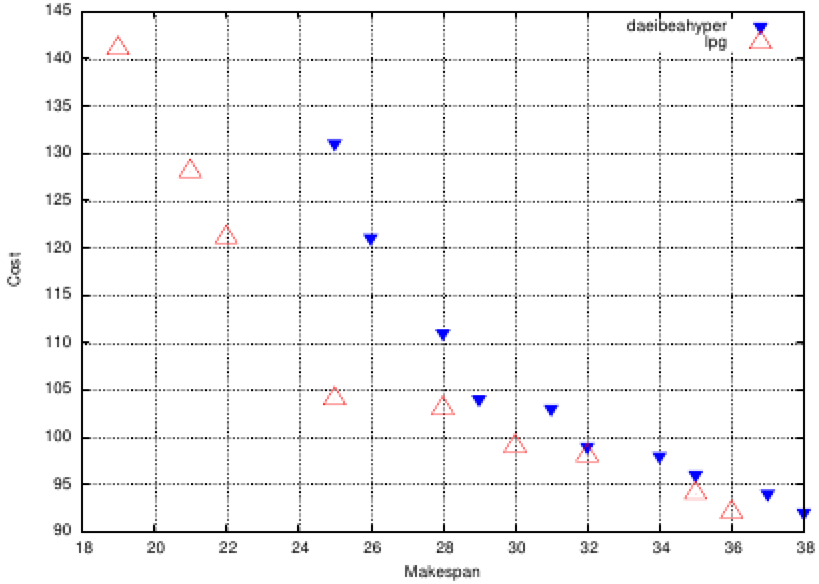
Solution set for MO-DAE on Elevators10

(LPG fails on instances > 01)

Comparison with LPG (3)



(g) pfile0-floortile

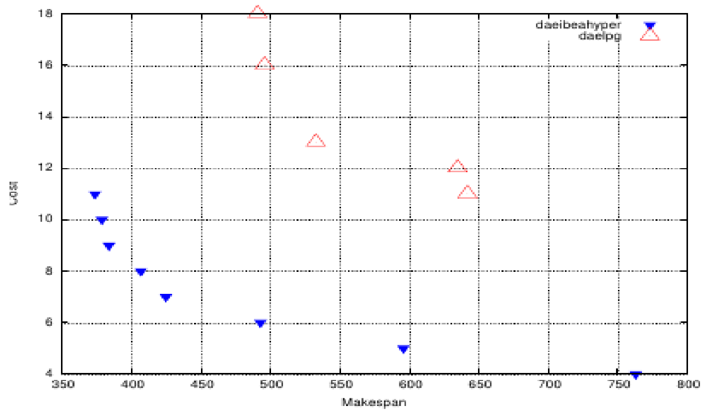


(h) pfile3-floortile

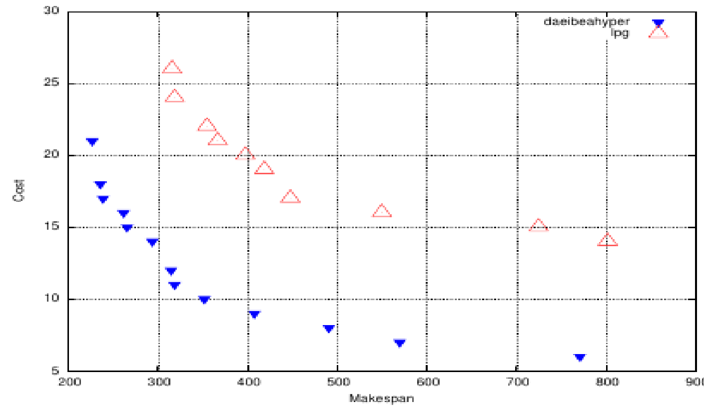
Pareto Fronts for MO-DAE and LPG

on FloorTiles problems

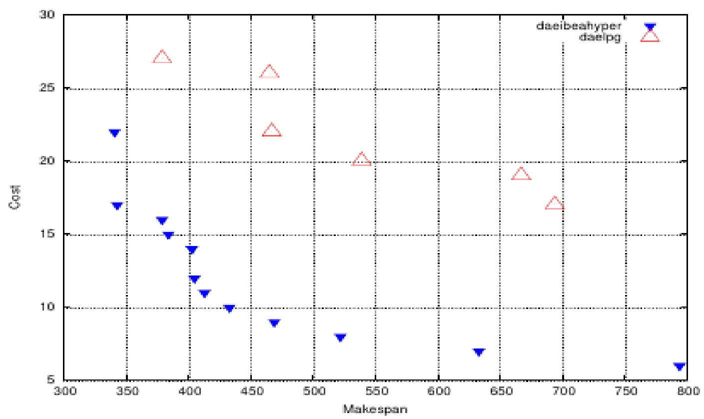
Comparison with LPG (4)



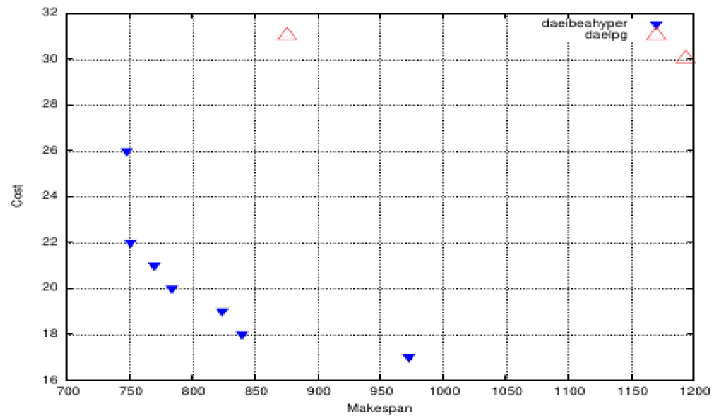
(f) p01-openstacks



(c) p05-openstacks



(e) p10-openstacks

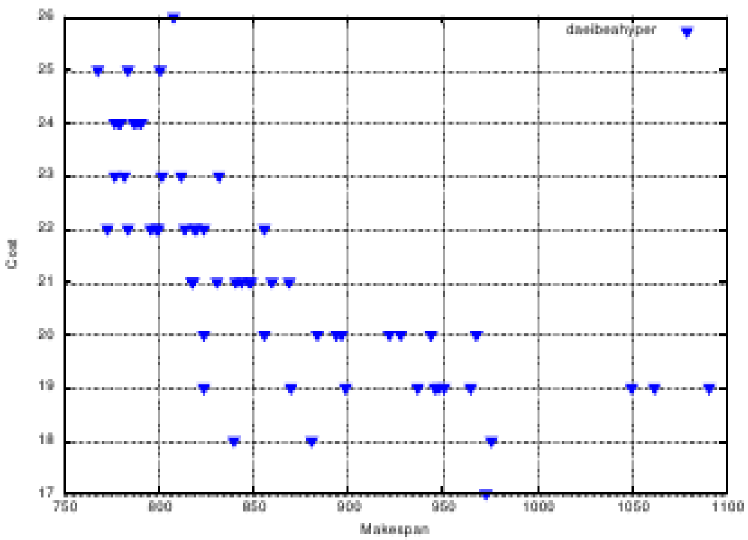


(d) p15-openstacks

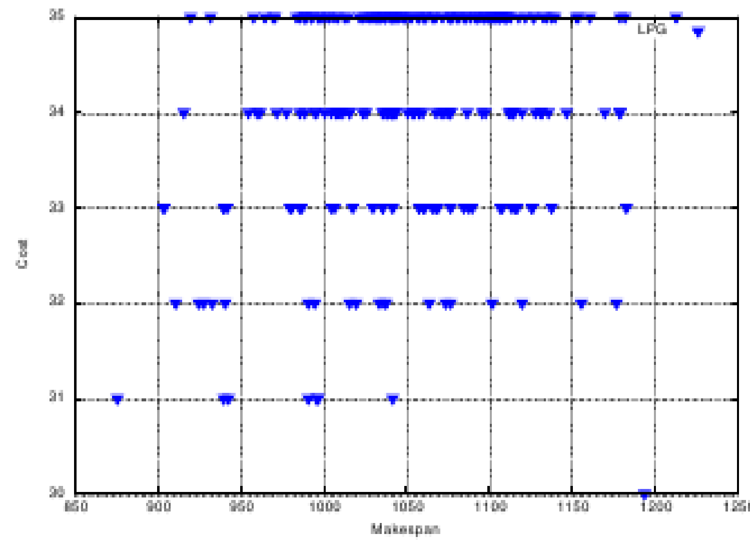
Paerto Fronts for MO-DAE vs LPG

on OpenStacks problems

Comparison with LPG (5)



(e) OPENSTACKS15: DAE



(f) OPENSTACKS15: LPG

Solution sets for MO-DAE and LPG on OpenStacks15

(scales are different)

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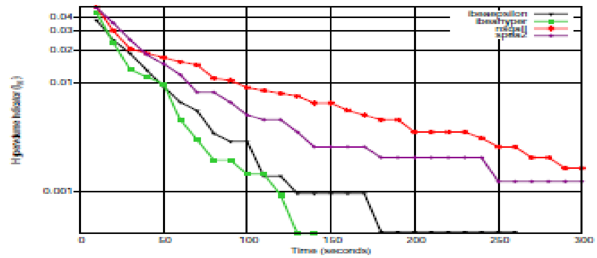
Summary

- MO-DAE-YAHSP : a multi-objective evolutionary planner based on a single-objective classical planner
- MiniZeno, a tunable MO benchmark
- Randomized YAHSP strategy
- IBEA-Hv best choice (on Zeno benchmarks)
- Outperforms aggregation approaches
  - Single-objective DAE
  - Metric-sensitive LPG

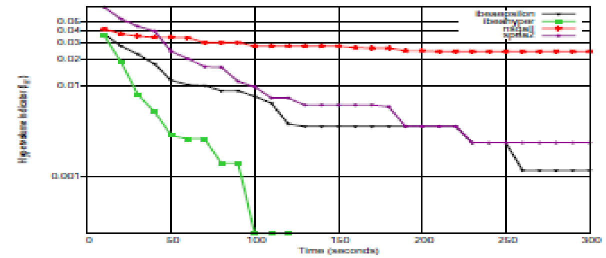
Perspectives

- Extended experiments on large IPC instances
  - What happens on FloorTiles Problems?
- Self-adaptive choice of YAHSP strategy
  - Individual or sub-goal level?
- On-line setting of (other) parameters
  - Adaptive operator selection
- Better handling of risk
  - Smoothing the needle effect

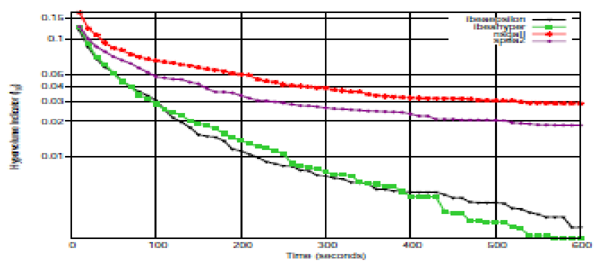
Comparative Results



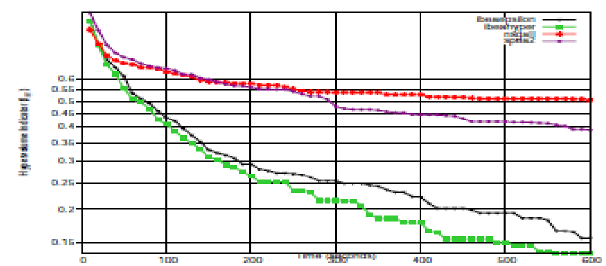
(a) MULTIZENO3$_{cost}$



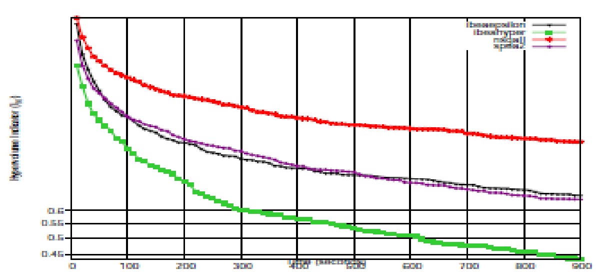
(b) MULTIZENO3$_{risk}$



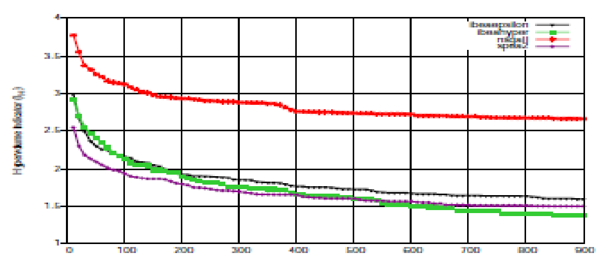
(c) MULTIZENO6$_{cost}$



(d) MULTIZENO6$_{risk}$



(e) MULTIZENO9$_{cost}$



(f) MULTIZENO9$_{risk}$

Evolution of hypervolume / reference set for all 4 MOEAs

Statistical tests

Instances	Algorithms	Algorithms: $NSGAII$	Algorithms: $IBEA_{\varepsilon+}$	Algorithms: $IBEA_{H-}$	Algorithms: $SPEA2$
$Zeno3_{cost}$	$NSGAII$	$-$	$\equiv$	$\equiv$	$\equiv$
	$IBEA_{\varepsilon+}$	$\equiv$	$-$	$\equiv$	$\equiv$
	$IBEA_{H-}$	$\equiv$	$\equiv$	$-$	$\equiv$
	$SPEA2$	$\equiv$	$\equiv$	$\equiv$	$-$
$Zeno3_{risk}$	$NSGAII$	$-$	$\equiv$	$\equiv$	$\equiv$
	$IBEA_{\varepsilon+}$	$\equiv$	$-$	$\equiv$	$\succ$
	$IBEA_{H-}$	$\equiv$	$\equiv$	$-$	$\succ$
	$SPEA2$	$\equiv$	$\prec$	$\prec$	$-$
$Zeno6_{cost}$	$NSGAII$	$-$	$\prec$	$\prec$	$\prec$
	$IBEA_{\varepsilon+}$	$\succ$	$-$	$\equiv$	$\equiv$
	$IBEA_{H-}$	$\succ$	$\equiv$	$-$	$\equiv$
	$SPEA2$	$\succ$	$\equiv$	$\equiv$	$-$
$Zeno6_{risk}$	$NSGAII$	$-$	$\prec$	$\prec$	$\equiv$
	$IBEA_{\varepsilon+}$	$\succ$	$-$	$\succ$	$\succ$
	$IBEA_{H-}$	$\succ$	$\prec$	$-$	$\succ$
	$SPEA2$	$\equiv$	$\prec$	$\prec$	$-$
$Zeno9_{cost}$	$NSGAII$	$-$	$\prec$	$\prec$	$\prec$
	$IBEA_{\varepsilon+}$	$\succ$	$-$	$\prec$	$\equiv$
	$IBEA_{H-}$	$\succ$	$\succ$	$-$	$\equiv$
	$SPEA2$	$\succ$	$\equiv$	$\equiv$	$-$
$Zeno9_{risk}$	$NSGAII$	$-$	$\prec$	$\prec$	$\prec$
	$IBEA_{\varepsilon+}$	$\succ$	$-$	$\prec$	$\equiv$
	$IBEA_{H-}$	$\succ$	$\succ$	$-$	$\equiv$
	$SPEA2$	$\succ$	$\equiv$	$\equiv$	$-$

Ibea-Hv performs significantly better