Theoretical Issues of Evolutionary Multiobjective Optimization: Selected Research Topics and Open Problems

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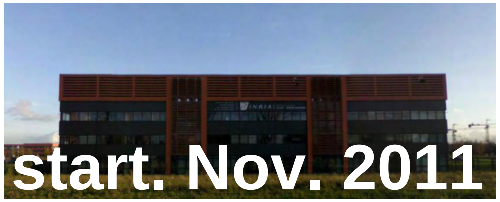
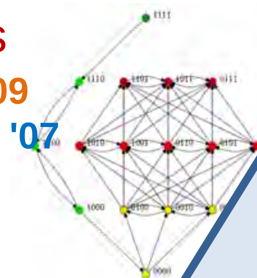


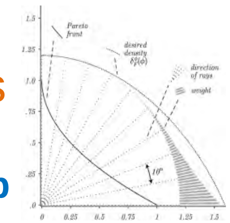
Contributions in EMO

Theory
chapter '10

Runtime analyses
IEEE-TEC '09
ACM-GECCO '07

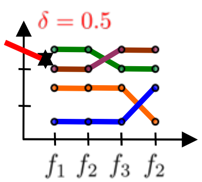


optimal μ-distributions
ACM-FOGA '09
ACM-GECCO '09b
PPSN '10b
TCS '11
SEAL'10

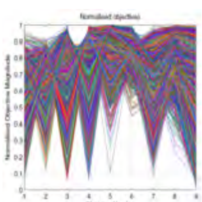


Runtime analyses
PPSN '08

Many-Objective Optimization and Objective Reduction



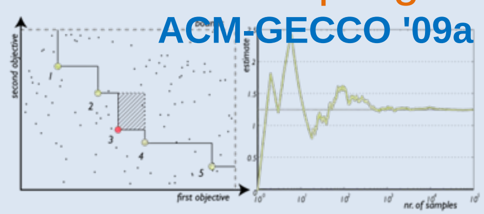
ECJ '09
chapter '07
PPSN '06
IEEE-CEC '07
MOPGP '08
OR '06



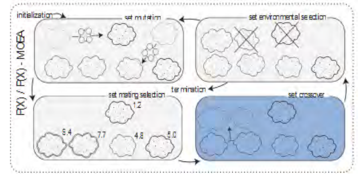
Hypervolume-Based Search

PhD thesis '09

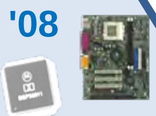
Hypervolume Sampling
ACM-GECCO '09a

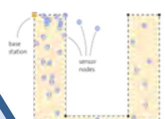


Set-Based EAs
EMO '09

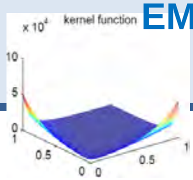


Network processor
ACM-GECCO '08

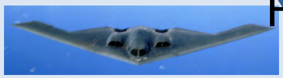




Weighted Hypervolume
EMO '07



Wireless Sensor Networks
MCDM '08



Hazmat Routing
CTW '11

Radar Waveforms

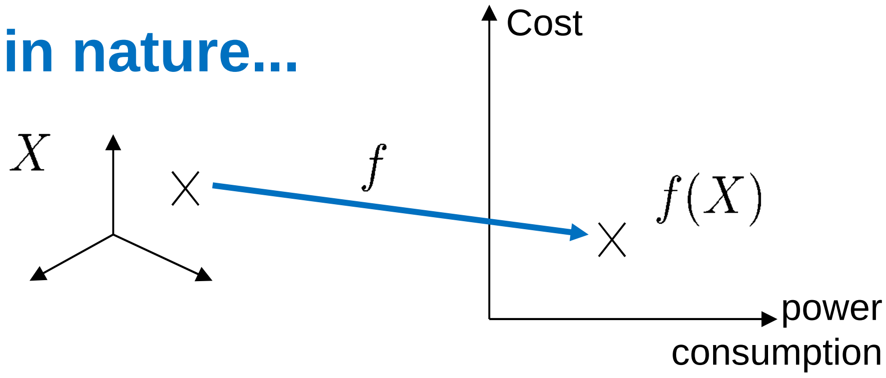
Algorithms

Applications

Blackbox Optimization

Most problems are multiobjective in nature...

$$\min_{x \in X} f(x) = (f_1(x), \ldots, f_k(x)) \in \mathbb{R}^k$$



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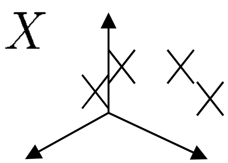

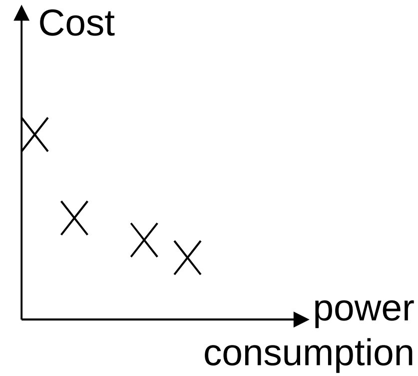

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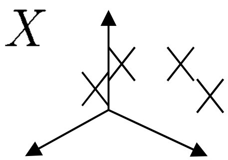

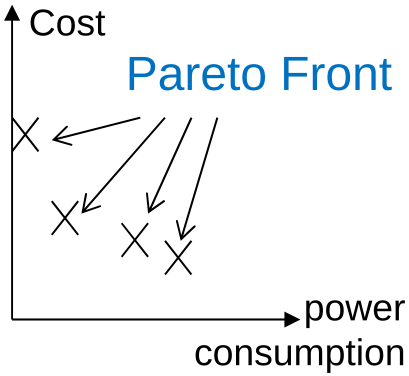

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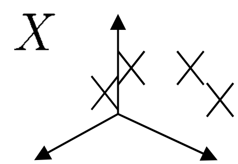

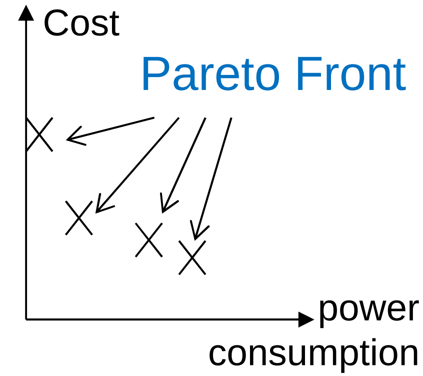

Issues:

non-linear

noisy

objectives

non-differentiable

expensive
(e.g. simulations)

many objectives

problem

huge search spaces

many constraints

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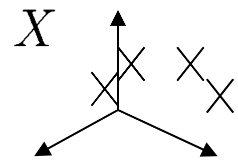

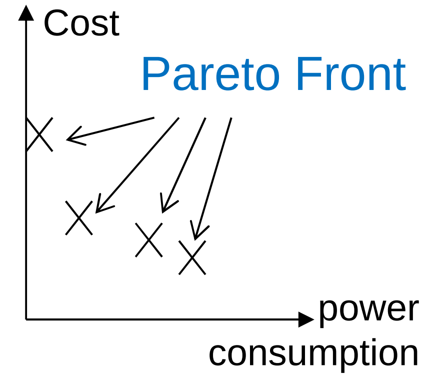

Blackbox optimization

$$x \in X \rightarrow \boxed{f} \rightarrow (f_1(x), \ldots, f_k(x))$$

?

Features:

- function f used as an *oracle*
- only mild locality assumptions

Blackbox Optimization

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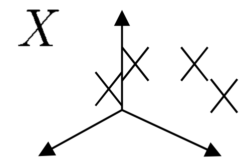

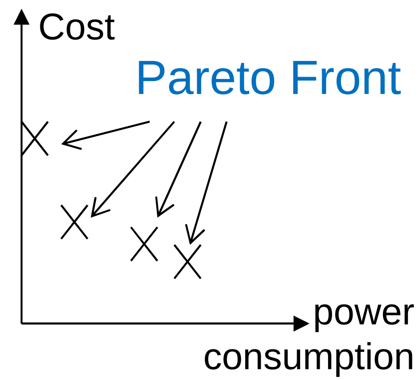

Blackbox optimization

$$x \in X \rightarrow \boxed{f} \rightarrow (f_1(x), \dots, f_k(x))$$

?

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Evolutionary Multiobjective Optimization (EMO)

EMO =
randomized search heuristics
optimizing on solution **sets**

“sampling” the Pareto front
to **inform** decision maker

Main Purpose of My Talk

- Talk about some of my work
- A subjective list of “hot topics” in the theory of EMO
- Share interesting open questions and ideas

Why?

- build foundation for later discussions this week
- have content for possible collaborations/thesis topics

the GECCO deadline is soon ;-)

Overview

Benchmarking

"*on how to compare sets of solutions*"

Indicator-based Search and Preference Articulation

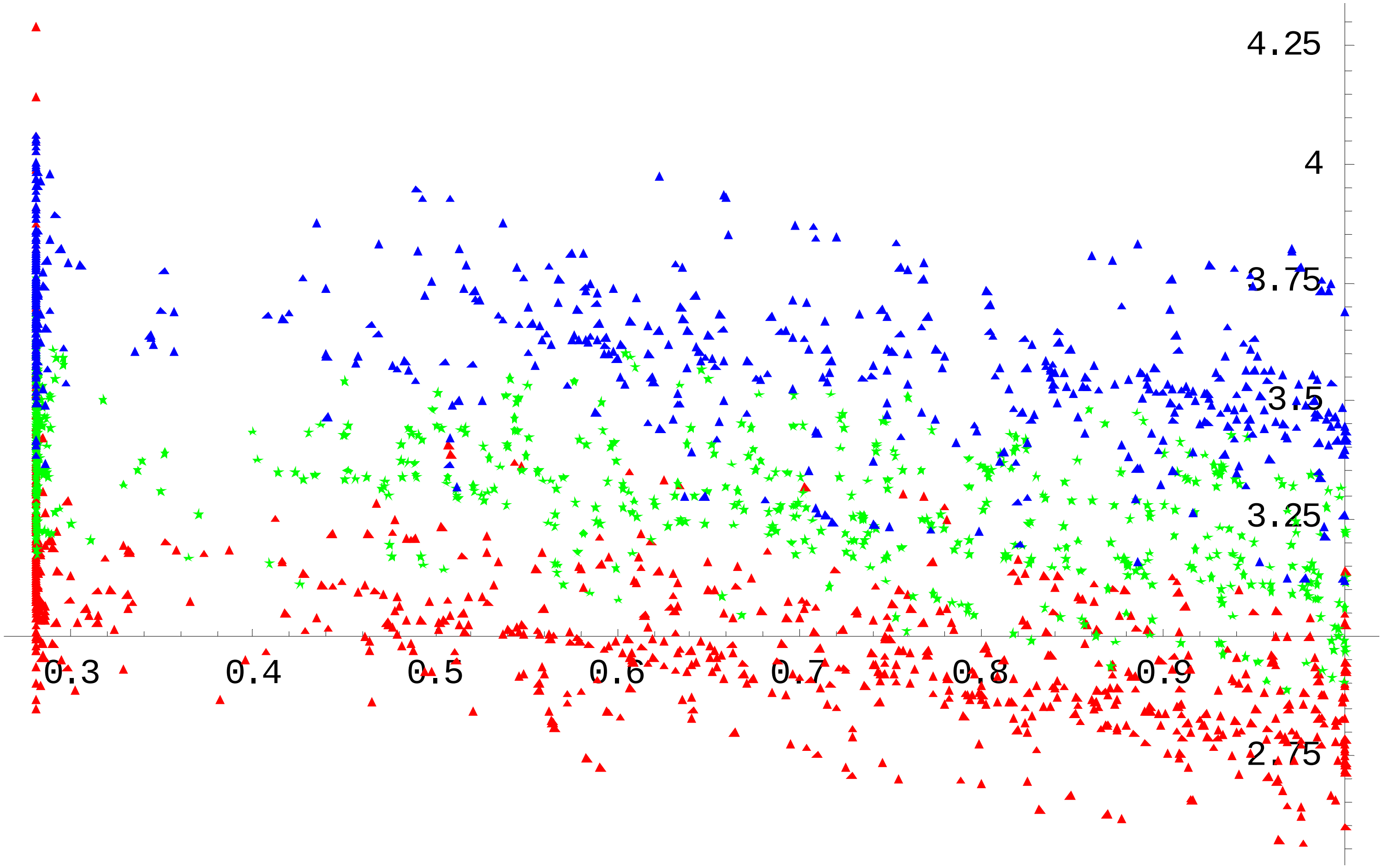
"*on how to optimize and steer the search in many-objective problems*"

Objective Reduction and Multiobjectivization

"on when to reduce and when to increase the number of objectives"

Once Upon a Time...

... multiobjective EAs were mainly compared visually:



ZDT6 benchmark problem: IBEA, SPEA2, NSGA-II

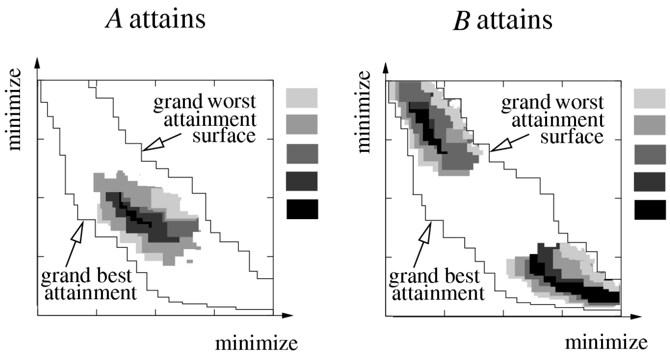
Two Approaches for Empirical Studies

Attainment function approach:

- Applies statistical tests directly to the samples of approximation sets
- Gives detailed information about how and where performance differences occur

Quality indicator approach:

- First, reduces each approximation set to a single value of quality
- Applies statistical tests to the samples of quality values

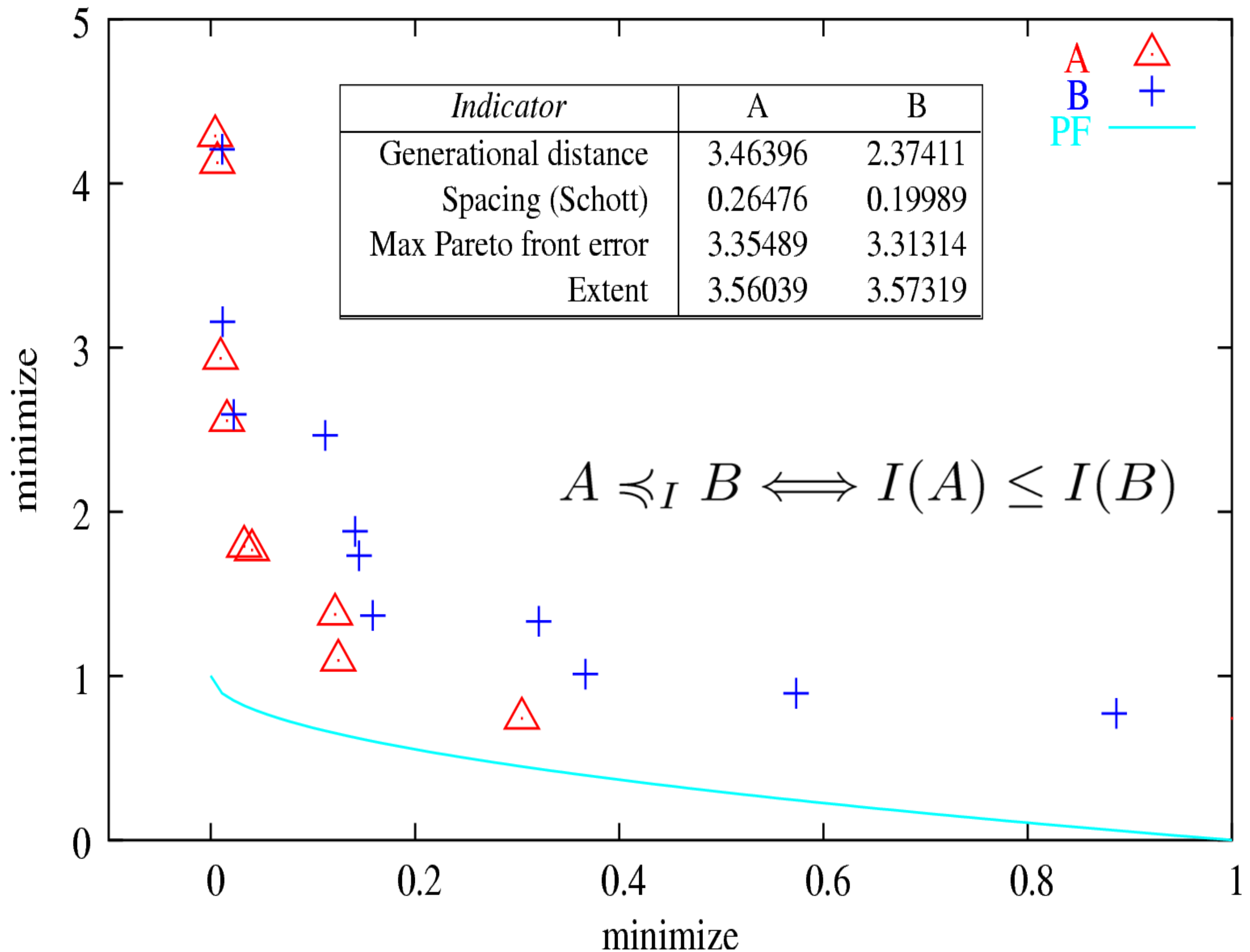


Indicator	A	B
Hypervolume indicator	6.3431	7.1924
ϵ-indicator	1.2090	0.12722
R_2 indicator	0.2434	0.1643
R_3 indicator	0.6454	0.3475

see e.g. [Zitzler et al. 2003]

Problem With Arbitrary Quality Indicators

Don't use an arbitrary quality indicator, but a meaningful one...



Indicator	A	B
Generational distance	3.46396	2.37411
Spacing (Schott)	0.26476	0.19989
Max Pareto front error	3.35489	3.31314
Extent	3.56039	3.57319

$$A \preccurlyeq_I B \iff I(A) \leq I(B)$$

Refinements

$\overset{\text{ref}}{\preccurlyeq}$ **refines** a preference relation $\preccurlyeq$ iff

$$A \preccurlyeq B \wedge B \not\preccurlyeq A \Rightarrow A \overset{\text{ref}}{\preccurlyeq} B \wedge B \overset{\text{ref}}{\not\preccurlyeq} A \qquad \textit{(better} \Rightarrow \textit{better)}$$

$\Rightarrow$ fulfills requirement

…sought are total refinements!

(such as the hypervolume indicator)

Optimality in Indicator-Based Search

but still...

- difficult to interpret absolute numbers
- better: relative values: how far from the optimum (as in single-obj. opt.)

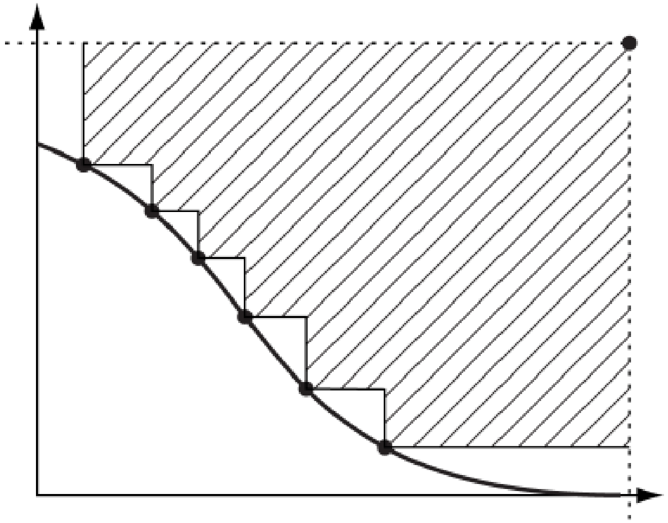
Question:

  - what is the optimum?

Optimal μ-Distributions

When the goal is to maximize the hypervolume…

- this yields sets with only Pareto-optimal solutions [Fleischer 2003]
- those sets, if unrestricted in size, cover the entire Pareto front
- many hypervolume-based EMO algorithms have a population size μ!



Optimal μ-Distribution:

A set of μ solutions that maximizes a certain (unary) indicator I among all sets of μ solutions is called optimal μ-distribution for I.

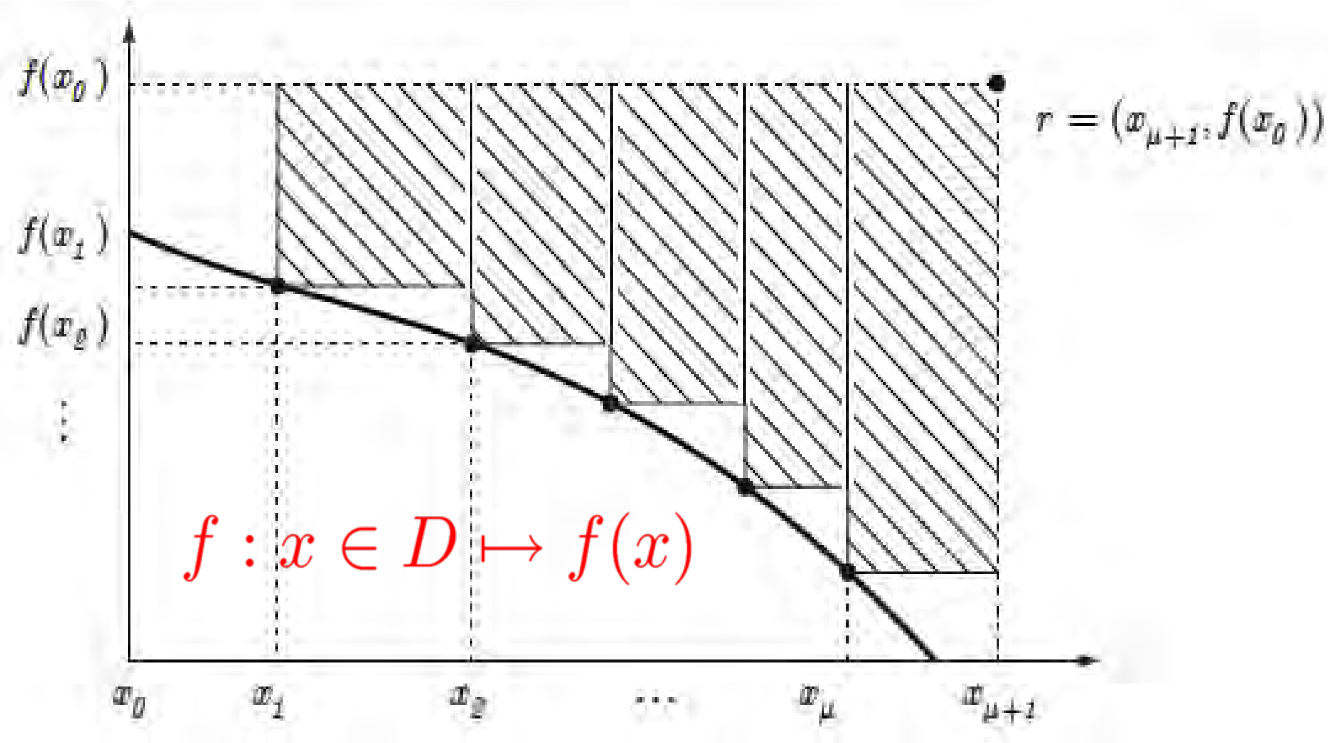
Optimal μ-Distributions

Questions:

- how are optimal μ-distributions characterized?
  - understand the bias of the indicator (influence on DM)
  - what is the influence of the indicator's parameters on optimal μ-distributions?
  - guidelines for practical usage
- do algorithms converge to optimal μ-distributions?

Notations for 2-Objective Case [Auger et al. 2009]

Results for 2 objectives only… (except [Auger et al. 2010])



hypervolume indicator:
$$I_H((x_1, \dots, x_\mu)) := \sum_{i=1}^{\mu} (x_{i+1} - x_i)(f(x_0) - f(x_i))$$

A Necessary Condition [Auger et al. 2009]

Proposition 1. **(Necessary condition for optimal μ-distributions)** *If f is continuous, differentiable and $(x_1^\mu, \ldots, x_\mu^\mu)$ denote the x-coordinates of a set of μ points maximizing the hypervolume indicator, then for all $x_{min} < x_i^\mu < x_{max}$*

$$f'(x_i^\mu)\left(x_{i+1}^\mu - x_i^\mu\right) = f(x_i^\mu) - f(x_{i-1}^\mu),\ i = 1 \ldots \mu \qquad (3)$$

where f' denotes the derivative of f, $f(x_0^\mu) = r_2$ and $x_{\mu+1}^\mu = r_1$.

Proof idea:

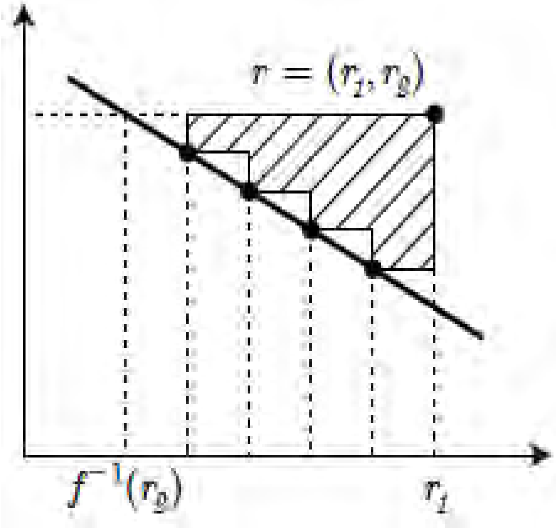
I_H max $\Rightarrow$ derivative is 0 at each x_i^μ or x_i^μ is at the boundary of the domain

Interpretation of Necessary Condition

Example: equal distances (only) on linear fronts

$$f : x \in [x_{min}, x_{max}] \mapsto \alpha x + \beta$$

$$\alpha \left(x^\mu_{i+1} - x^\mu_i\right) = f(x^\mu_i) - f(x^\mu_{i-1}) = \alpha(x^\mu_i - x^\mu_{i-1})$$



generalization of results in [Emmerich et al. 2005, Beume et al. 2007]

exact optimal μ-distribution for linear fronts and any choice of reference point [Brockhoff 2010]

A Density Result: When μ Goes to Infinity

Observation:

general front shapes too difficult to investigate for finite μ

Question:

can we characterize optimal μ-distributions with respect to a density $\delta(x) = \lim_{\substack{\mu\to\infty \\ h\to 0}} \left(\frac{1}{\mu h} \sum_{i=1}^{\mu} \mathbf{1}_{[x,x+h[}(x_i^\mu) \right)$?

[Auger et al. 2009]

Result and Interpretation

The resulting density is

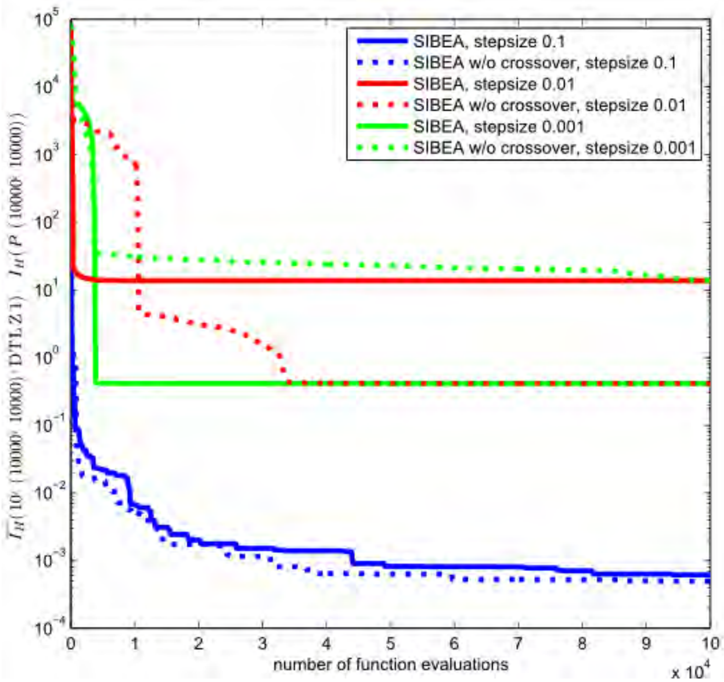
$$\delta(x) = \frac{\sqrt{-f'(x)}}{\int_0^{x_{max}} \sqrt{-f'(x)}dx}$$

How can we interpret this?

- bias only depends on slope of f *in contrast to* [Deb et al. 2005, Zitzler and Thiele 1998]
- density highest where slope = 45° *compliant to* [Beume et al. 2007]
- experimental results for finite and small μ support the result

Implications for Benchmarking

- now we can transform multiobjective benchmarking into a single-objective problem (where we sometimes know the optimum)
- we can use exactly the same methodology than for single-objective benchmarking:
  - horizontal view (i.e., fixing target values instead of runtime)
  - ERT
  - performance plots a la BBOB



Observation:

we are not as advanced in EMO as in single-objective optimization

Open Questions

Optimal μ-distributions

- uniqueness proofs
- other test problems & other indicators
- >2D
- efficient calculation/approximation
- ‘numbers’ for practical usage (on web page?)

Linear convergence speed

- what’s the problem in current algorithms?
- how to achieve it?

Others

- “good” test functions
- multiobjective BBOB
- effective restarts in EMO

Overview

Indicator-based Search and Preference Articulation

“*on how to optimize and steer the search in many-objective problems*”

Indicator-Based Search

Assume, we have chosen a total refinement and therefore an optimization goal

- how to achieve it as fast as possible?

Example: hypervolume indicator

- SMS-EMOA (changing the reference point might be bad?!)
- Even with fixed reference point, greedy selection might be bad
- HypE (?!)
- Something else?
- Isn’t the variation operator even more important?

Needed:

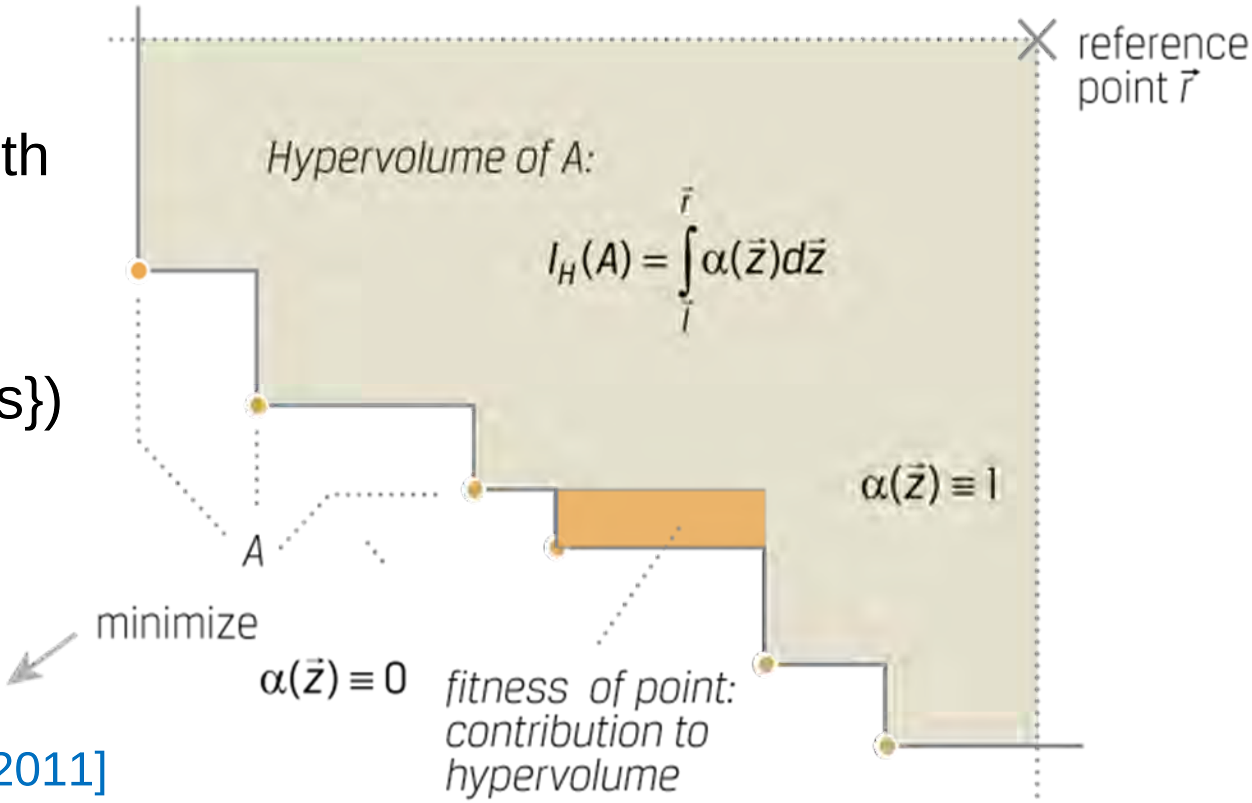
- better understanding of what’s happening in search
- (first) examples of runtime analyses/convergence speed

Idea of Hypervolume-Based Selection

Main Idea (SMS-EMOA, MO-CMA-ES, HypE, …)

use hypervolume indicator to guide the search: refinement!

Delete solutions with the smallest hypervolume loss $d(s) = I_H(P)-I_H(P / \{s\})$ iteratively



But: can result

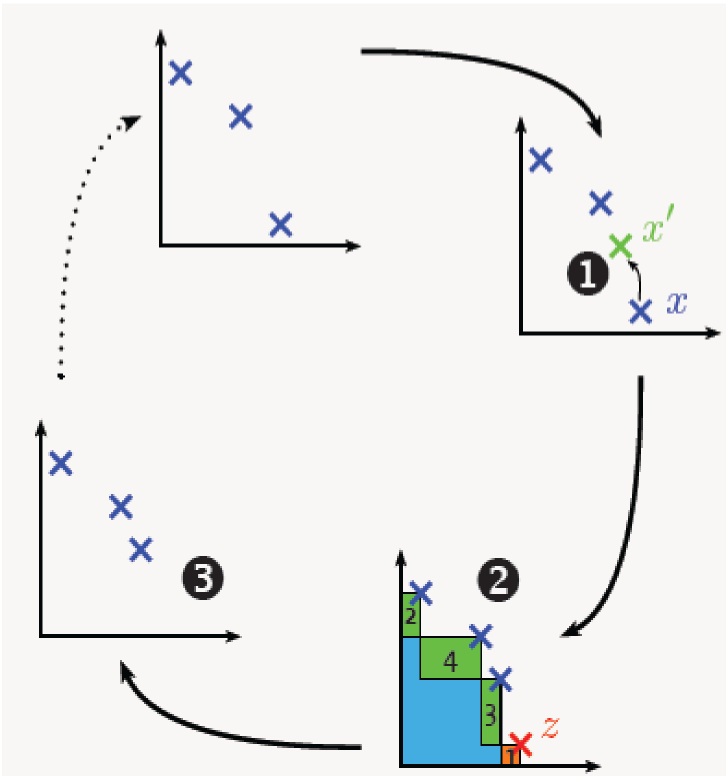
in cycles [Judt et al. 2011]

is expensive [Bringmann and Friedrich 2008]

and can result in arbitrarily bad sets compared to the optimal one

[Bringmann and Friedrich 2009]

A Simple Algorithm: SIBEA



(μ+1)SIBEA

generate initial population $P \subseteq \{0,1\}^n$ at random

repeat:

❶ mutate randomly selected $x \in P$ to x' by flipping each bit of x with probability $1/n$

$P' = P \cup \{x'\}$

❷ for all solutions $x \in P$, determine the hypervolume loss $d(x) = I_H(P') - I_H(P' \setminus \{x\})$

❸ choose a $z \in P$ with smallest loss $d(z)$

$P = P' \setminus \{z\}$

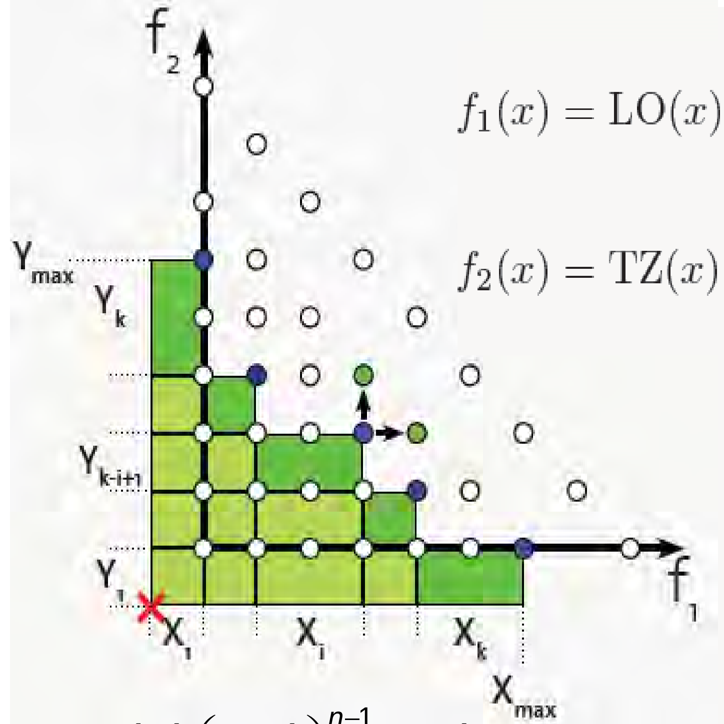
Properties:

- No worsenings of I_H
- Duplicated solutions removed first
- Selection similar to SMS-EMOA [Emmerich et al. 2005] and MO-CMA-ES [Igel et al. 2007]

Runtime Analysis of SIBEA on LOTZ

Theorem [Brockhoff et al. 2008]**:**

If μ≥n+1, the (μ+1)SIBEA optimizes LOTZ in O(μn^2) generations.



$$f_1(x) = \mathrm{LO}(x) = \sum_{i=1}^{n} \prod_{j=1}^{i} x_j$$

$$f_2(x) = \mathrm{TZ}(x) = \sum_{i=1}^{n} \prod_{j=i}^{n} (1 - x_j)$$

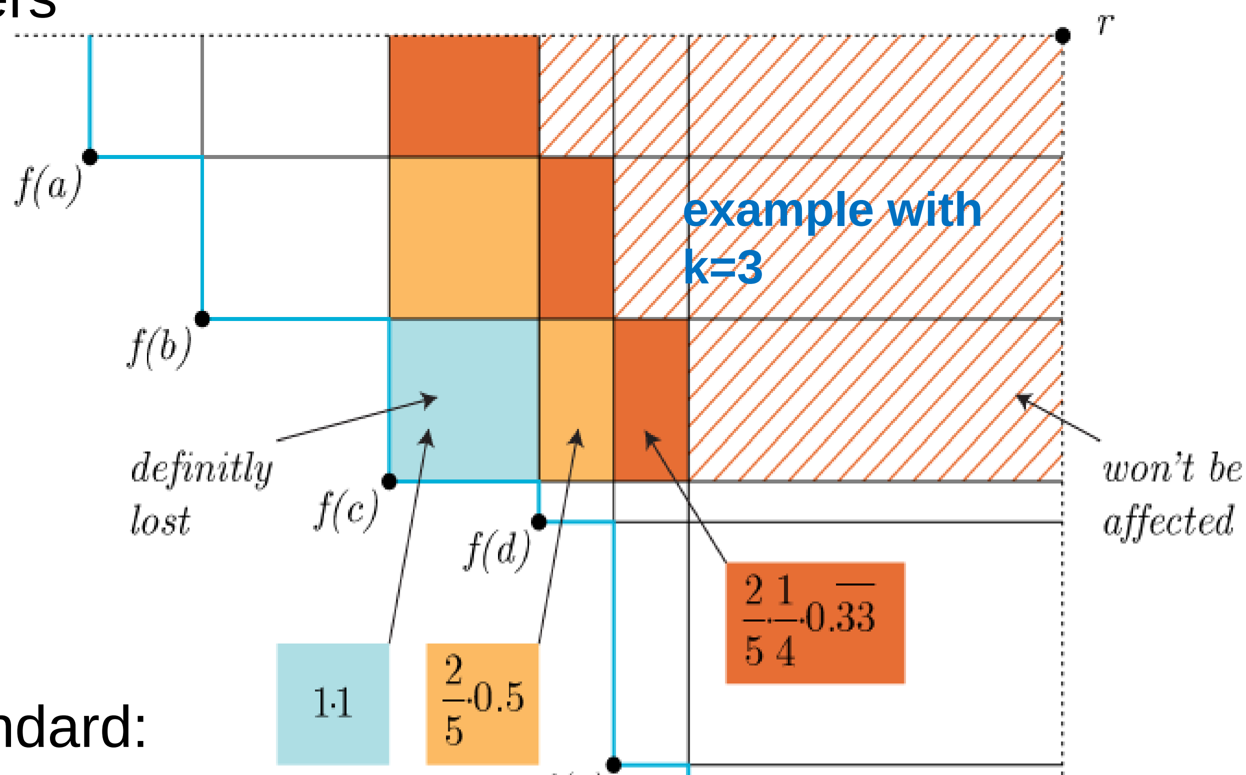
Sketch of Proof:

- 2k mutations increase I_H (prob. $\frac{1}{\mu}\frac{1}{n}\left(1-\frac{1}{n}\right)^{n-1} \geq \frac{1}{e\mu n}$)
- Total increase $\geq \max\{X_{\max}, Y_{\max}\} \geq \sqrt{X_{\max} \cdot Y_{\max}} \geq \sqrt{I_H}$
- Exp. increase for 1 mutation $\geq \sqrt{I_H}/2k$; with Markov: i.e., in 8k good mutations $\sqrt{I_H}$ w.h.p.
- Exp. runtime for increase by $\sqrt{I_H}$ is $O\left(\frac{\mu n}{2k} \cdot 8k\right) = O(\mu n)$
- By induction, O(n) such increases sufficient to reach front, then O(μn) time enough to find all other n points

A More Involved Selection Scheme: HypE

Idea [Bader and Zitzler 2011]

Solution quality = expected loss, when removing the point and (randomly) k-1 others



Comparison HypE/standard:

	opt.	dist	better
new	59.7%	0.00109	30.2%
standard	44.5%	0.00261	3.2%

Question:
can we show the improvement also theoretically?

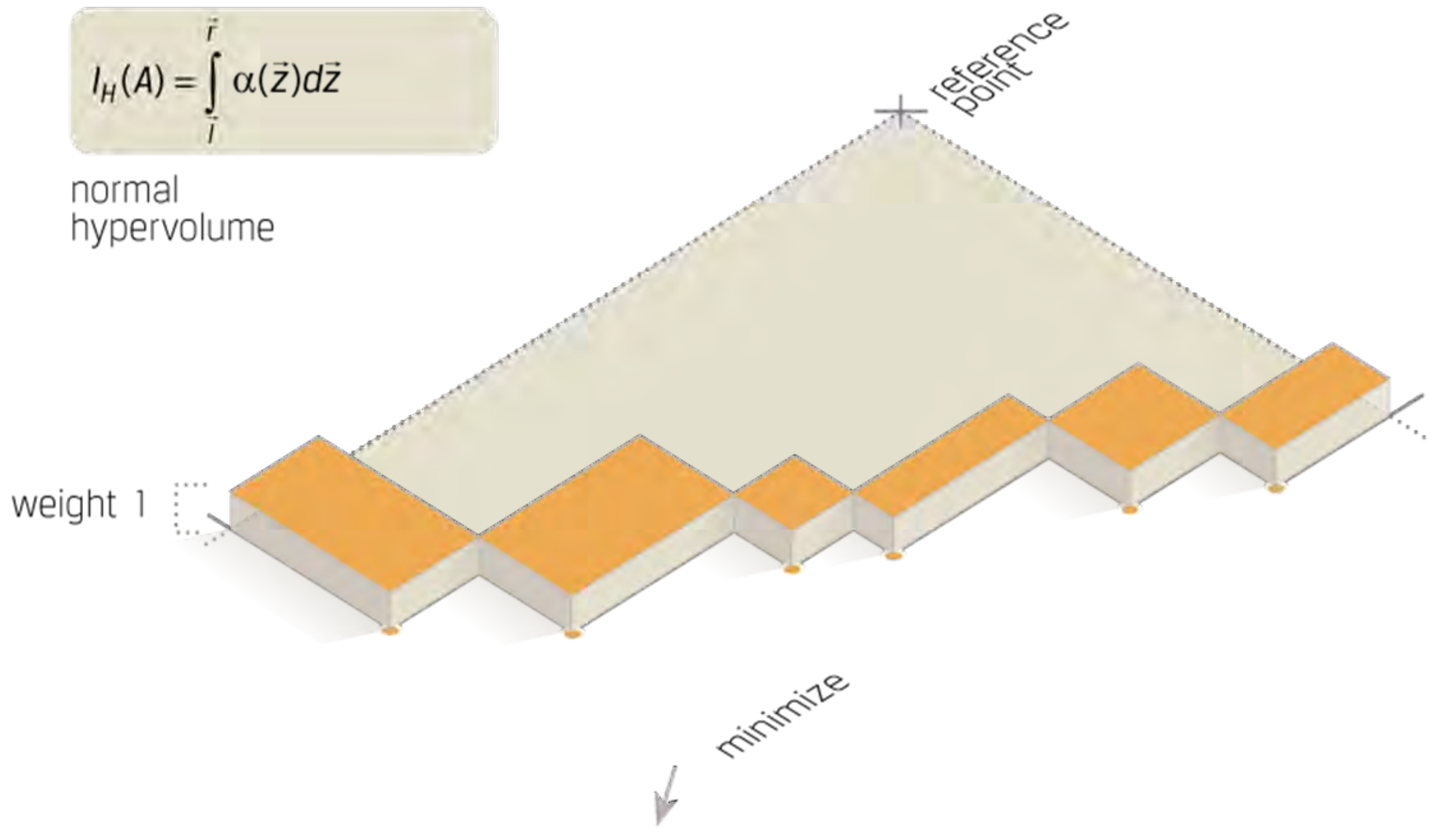
Articulating User Preferences

What if user wants something else than finding the optimal μ-distribution for the hypervolume indicator? E.g.

- (p)reference points
- stressing extremes
- simulate classical scalarizing function approaches

Idea:

[Zitzler et al. 2007]



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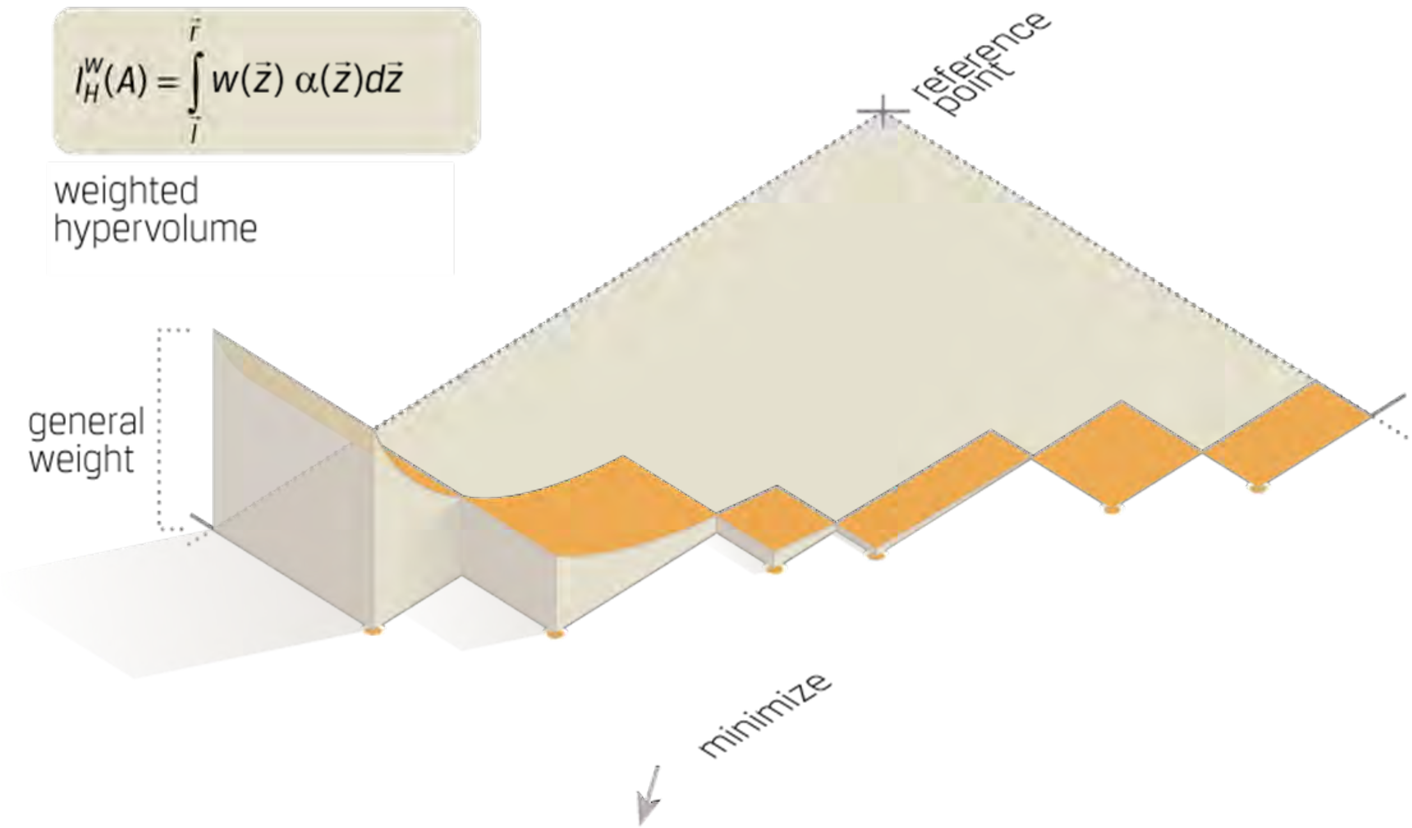
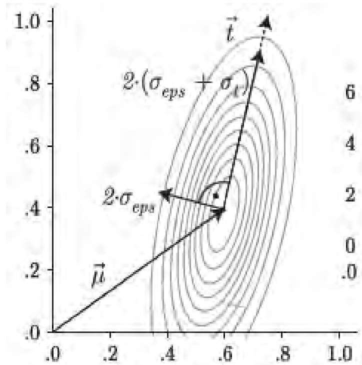
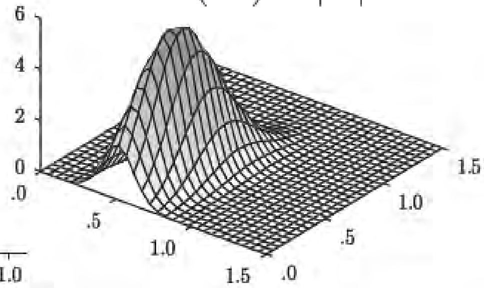
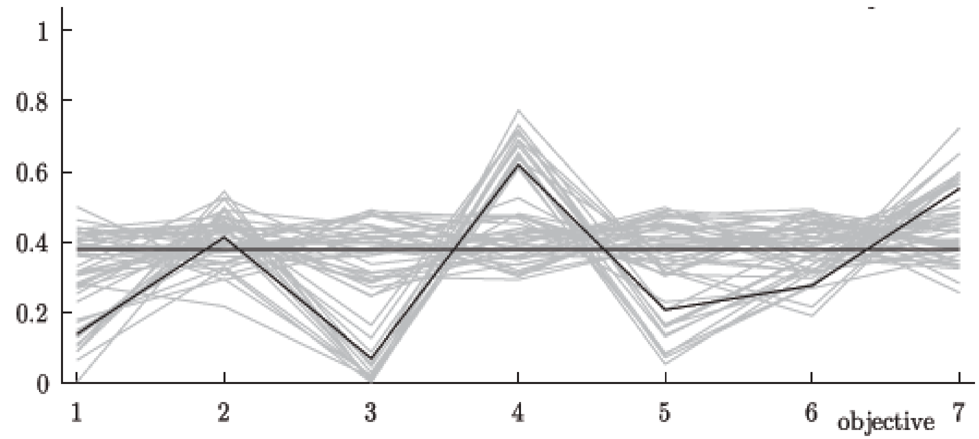


preference point

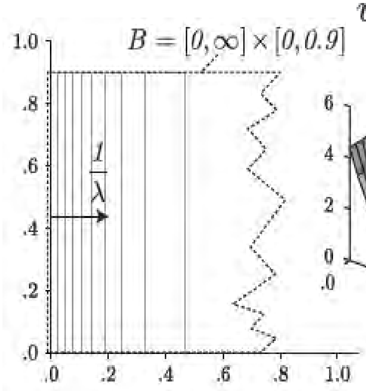


$$w(\vec{z}) = \frac{1}{(2\pi)^{k/2}|C|^{1/2}} e^{-\frac{1}{2}}$$

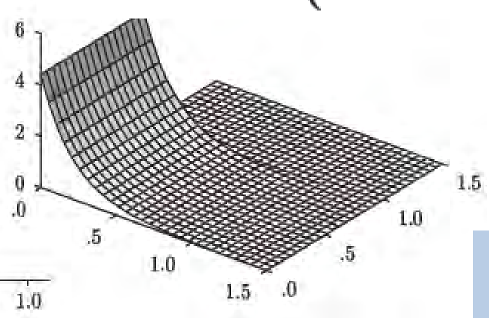


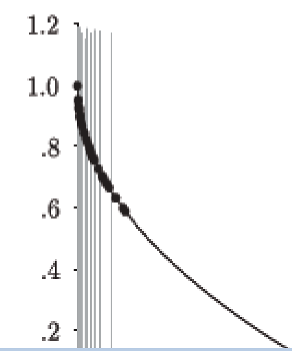


stressing one objective



$$w(z_1,\cdots,z_k) = \begin{cases} \left(\prod_{i\neq s}(b_i^u - b_i^l)\right)^{-1} \lambda e^{-\lambda(z_s - b_s^l)} & \vec{z}\in B \\ 0 & \vec{z}\notin B \end{cases}$$

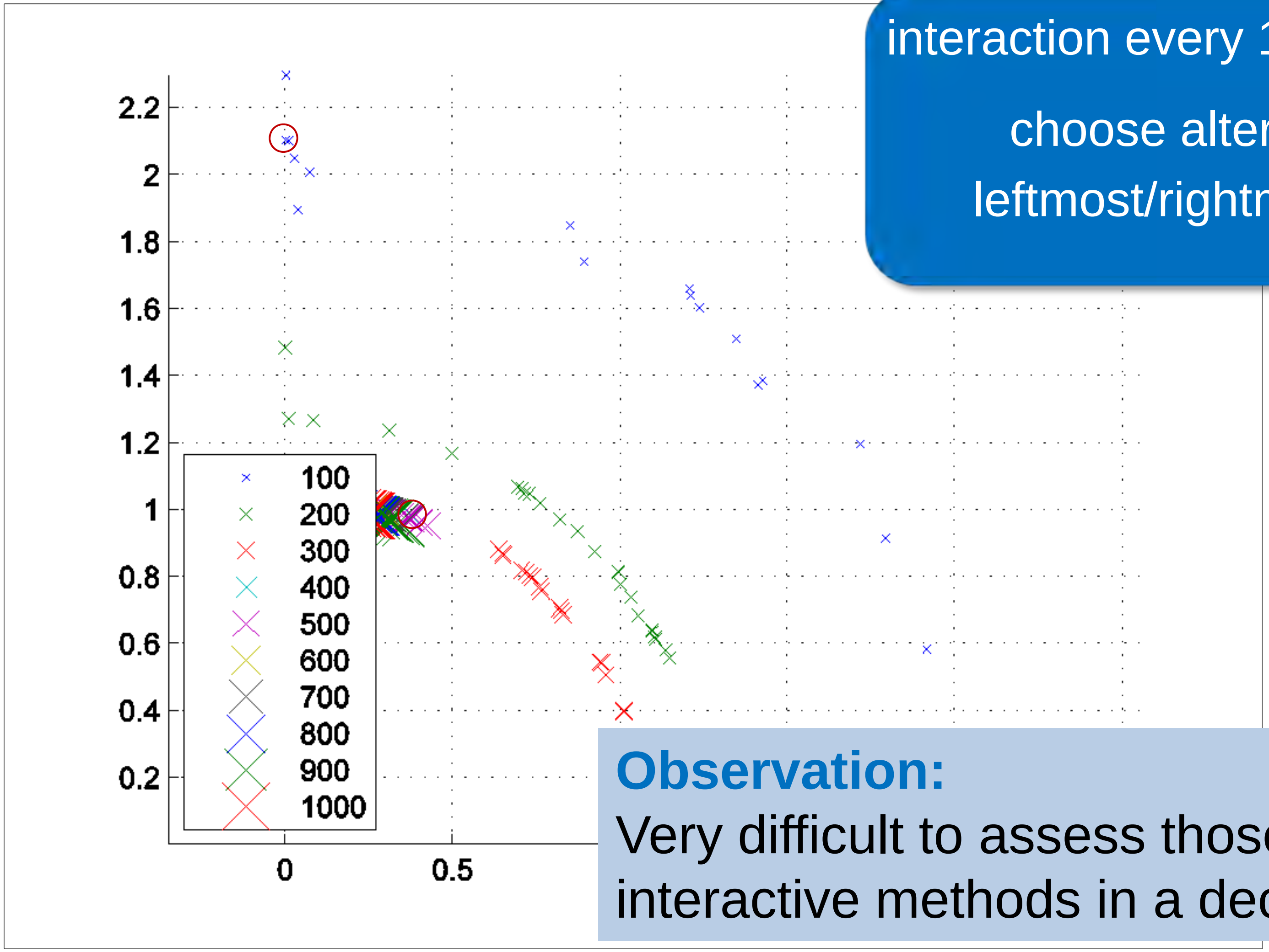




Question:
Does this work also interactively?

Some Experimental Results

Preliminary results shows yes:



interaction every 100 iterations:

choose alternatively leftmost/rightmost point

Observation:
Very difficult to assess those interactive methods in a decent way

Open Questions

HypE

- why is HypE better than normal HYP-based selection?
- and when? (Is there an example where it's provably better?)
- by how much (convergence speed?)
- greedy vs. oneShot: advantages and disadvantages
- a more advanced scheme than assuming uniform deletion?

SMS-EMOA: does algo becomes faster if HYP worsenings are not allowed (eg. by keeping old population if new one is worse)?

Convergence to optimal μ-distribution

- do other algorithms converge to optimal μ-distribution for other indicators?

Others

- more runtime analyses of indicator-based EMO
  - weighted hypervolume → reduced pop size of SEMO?
- preferences: how to evaluate/compare algos objectively?

Overview

Objective Reduction and Multiobjectivization

“on when to reduce and when to increase the number of objectives”

Adding Objectives: Common Belief…

Statements are contradictory: some studies say that…

problems may become harder

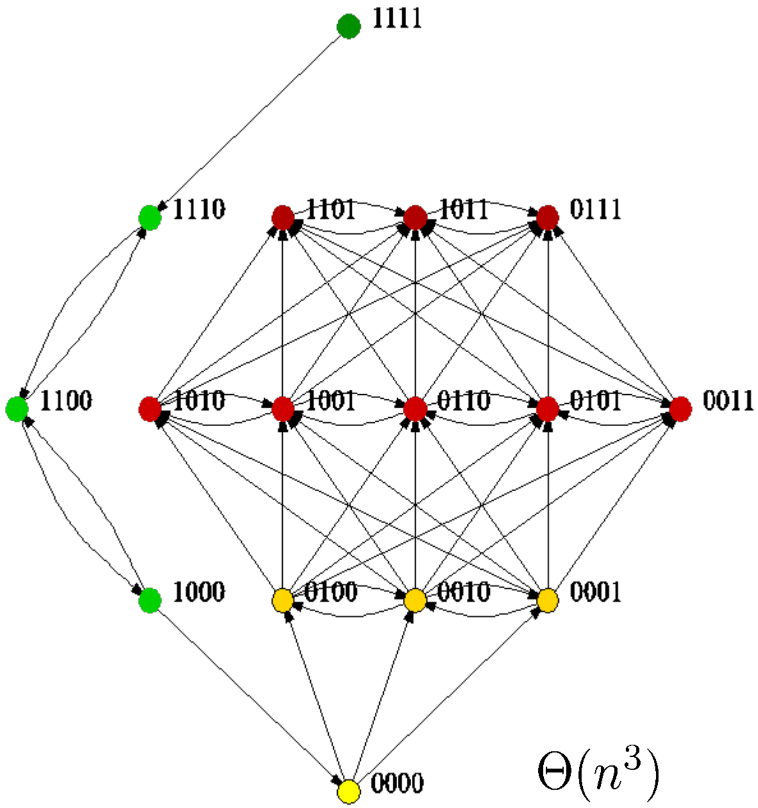
- [Fonseca and Fleming 1995], [Deb 2001], [Coello et al. 2002], and others:
  - conflicts between objectives
  - Pareto front size
  - # incomparable solutions
- [Winkler 1985]:
  - *theoretical work for random objectives*

problems may become easier

- [Knowles et al. 2001]:
  - multiobjectivization
- [Jensen 2004]:
  - helper-objectives
- [Scharnow et al. 2002], [Neumann and Wegener 2006]:
  - theoretical investigations
  - 2D faster than 1D
  - decomposition

Adding Objectives: Runtime Analysis

$$\text{PLATEAU}_1(x) := \begin{cases} |x|_0 & : \; x \notin \{1^i 0^{n-i}, 1 \leq i \leq n\} \\ n+1 & : \; x \in \{1^i 0^{n-i}, 1 \leq i < n\} \\ n+2 & : \; x = 1^n. \end{cases}$$



$\Theta(n^3)$

Add $\text{ONEMAX}(x)$

Faster: $O(n^2 \log n)$

Add $\text{ZEROMAX}(x)$

Slower: exponential w.h.p.

Conclusions When Adding Objectives

Additional objectives can:

- turn a region with direction into a plateau of incomparable solutions
- add direction to a plateau of indifferent solutions

Contrary, removing objectives can do the opposite

- and therefore might also reduce the optimization time
- interesting: removing objectives results in a refinement !

Several works on **automated objective reduction**

- for reducing the runtime of hypervolume-based methods in many-objective optimization
- for giving insights into the problem for the decision maker

Open Questions

- faster aggregation heuristics
- what happens exactly when aggregating objectives?
  - which orders can be generated by e.g. a weighted sum?
- test problems with changing conflict
- GUI for decision support (incl. innovization?)
- online reduction:
  - when to delete, when to add objectives? (MAB problem)
- more examples of multiobjectivization:
  - both with runtime analysis + experimental

Conclusions

- Three aspects of Theory in EMO
  - benchmarking
  - indicator-based search and preference articulation
  - objective reduction and multiobjectivization

- Many open questions
- Lots of ideas for future work

...let's do it ☺

Announcement

French Summer School in Evolutionary Algorithms

June 12-15, 2012
Quiberon (Bretagne)

organizers: D. Brockhoff, L. Jourdan, A. Liefooghe, S. Verel

Questions?

References

[Auger et al. 2009] A. Auger, J. Bader, D. Brockhoff, and E. Zitzler. **Theory of the Hypervolume Indicator: Optimal μ-Distributions and the Choice of the Reference Point**. In *Foundations of Genetic Algorithms (FOGA 2009)*, pages 87–102, New York, NY, USA, 2009. ACM

[Auger et al. 2010] A. Auger, J. Bader, and D. Brockhoff. **Theoretically Investigating Optimal μ-Distributions for the Hypervolume Indicator: First Results For Three Objectives**. In R. Schaefer et al., editors, *Conference on Parallel Problem Solving from Nature (PPSN XI)*, volume 6238 of *LNCS*, pages 586–596. Springer, 2010

[Bader and Zitzler 2011] J. Bader and E. Zitzler. **HypE: An Algorithm for Fast Hypervolume-Based Many-Objective Optimization**. *Evolutionary Computation* 19(1):45-76, 2011

[Beume et al. 2007] N. Beume, B. Naujoks, and M. Emmerich. **SMS-EMOA: Multiobjective Selection Based on Dominated Hypervolume**. *European Journal of Operational Research*, 181(3):1653–1669, 2007

[Bringmann and Friedrich 2008] K. Bringmann and T. Friedrich. **Approximating the Volume of Unions and Intersections of High-Dimensional Geometric Objects**. In S. H. Hong, H. Nagamochi, and T. Fukunaga, editors, *International Symposium on Algorithms and Computation (ISAAC 2008)*, volume 5369 of *LNCS*, pages 436–447, Berlin, Germany, 2008. Springer

[Bringmann and Friedrich 2009] K. Bringmann and T. Friedrich. **Don't Be Greedy When Calculating Hypervolume Contributions**. In *Foundations of Genetic Algorithms (FOGA 2009)*, pages 103–112. ACM, 2009

[Brockhoff 2010] D. Brockhoff. **Optimal μ-Distributions for the Hypervolume Indicator for Problems With Linear Bi-Objective Fronts: Exact and Exhaustive Results**. In *Simulated Evolution and Learning (SEAL 2010)*. Springer, 2010

[Brockhoff et al. 2008] D. Brockhoff, T. Friedrich, and F. Neumann. **Analyzing Hypervolume Indicator Based Algorithms**. In G. Rudolph et al., editors, *Conference on Parallel Problem Solving From Nature (PPSN X)*, volume 5199 of *LNCS*, pages 651–660. Springer, 2008

References

[Coello et al. 2002] C. A. Coello Coello, D. A. Van Veldhuizen, and G. B. Lamont. **Evolutionary Algorithms for Solving Multi-Objective Problems**. Kluwer Academic Publishers, New York, 2002.

[Deb 2001] K. Deb. **Multi-Objective Optimization Using Evolutionary Algorithms**. Wiley, Chichester, UK, 2001.

[Deb et al. 2005] K. Deb, M. Mohan, and S. Mishra. **Evaluating the ε-Domination Based Multi-Objective Evolutionary Algorithm for a Quick Computation of Pareto-Optimal Solutions**. *Evolutionary Computation*, 13(4):501–525, 2005

[Emmerich et al. 2005] M. Emmerich, N. Beume, and B. Naujoks. **An EMO Algorithm Using the Hypervolume Measure as Selection Criterion**. In *Conference on Evolutionary Multi-Criterion Optimization (EMO 2005)*, volume 3410 of *LNCS*, pages 62–76. Springer, 2005

[Fleischer 2003] M. Fleischer. **The Measure of Pareto Optima. Applications to Multi-Objective Metaheuristics**. In C. M. Fonseca et al., editors, *Conference on Evolutionary Multi-Criterion Optimization (EMO 2003)*, volume 2632 of *LNCS*, pages 519–533, 2003. Springer

[Fonseca and Fleming 1995] C. M. Fonseca and P. J. Fleming. **An Overview of Evolutionary Algorithms in Multiobjective Optimization**. *Evolutionary Computation*, 3(1):1–16, 1995

[Igel et al. 2007] C. Igel, N. Hansen, and S. Roth. **Covariance Matrix Adaptation for Multi-objective Optimization**. *Evolutionary Computation*, 15(1):1–28, 2007

[Jensen 2004] M. T. Jensen. **Helper-Objectives: Using Multi-Objective Evolutionary Algorithms for Single-Objective Optimisation**. *Journal of Mathematical Modelling and Algorithms*, 3(4):323–347, 2004. Online Date Wednesday, February 23, 2005

[Judt et al. 2011] L. Judt, O. Mersmann, and B. Naujoks. **Non-monotonicity of obtained hypervolume in 1-greedy S-Metric Selection**. In: *Conference on Multiple Criteria Decision Making (MCDM 2011)*, abstract, 2011

References

[Knowles et al. 2001] J. D. Knowles, R. A. Watson, and D. W. Corne. **Reducing Local Optima in Single-Objective Problems by Multi-objectivization**. In E. Zitzler et al., editors, *Conference on Evolutionary Multi-Criterion Optimization (EMO 2001)*, volume 1993 of *LNCS*, pages 269–283, Berlin, 2001. Springer

[Neumann and Wegener 2006] F. Neumann and I. Wegener. **Minimum Spanning Trees Made Easier Via Multi-Objective Optimization**. *Natural Computing*, 5(3):305–319, 2006

[Scharnow et al. 2002] J. Scharnow, K. Tinnefeld, and I. Wegener. **Fitness Landscapes Based on Sorting and Shortest Path Problems**. In *Conference on Parallel Problem Solving from Nature (PPSN VII)*, volume 2439 of *LNCS*, pages 54–63. Springer, 2002

[Winkler 1985] P. Winkler. **Random Orders**. *Order*, 1(1985):317–331, 1985

[Zitzler et al. 2003] E. Zitzler, L. Thiele, M. Laumanns, C. M. Fonseca, and V. Grunert da Fonseca. **Performance Assessment of Multiobjective Optimizers: An Analysis and Review**. *IEEE Transactions on Evolutionary Computation*, 7(2):117–132, 2003

[Zitzler et al. 2007] E. Zitzler, D. Brockhoff, and L. Thiele. **The Hypervolume Indicator Revisited: On the Design of Pareto-compliant Indicators Via Weighted Integration**. In S. Obayashi et al., editors, *Conference on Evolutionary Multi-Criterion Optimization (EMO 2007)*, volume 4403 of *LNCS*, pages 862–876, Berlin, 2007. Springer

[Zitzler and Thiele 1998] E. Zitzler and L. Thiele. **Multiobjective Optimization Using Evolutionary Algorithms - A Comparative Case Study**. In *Conference on Parallel Problem Solving from Nature (PPSN V)*, volume 1498 of *LNCS*, pages 292–301, 1998