Optimization in Dynamic Environments

GECCO Tutorial 2004

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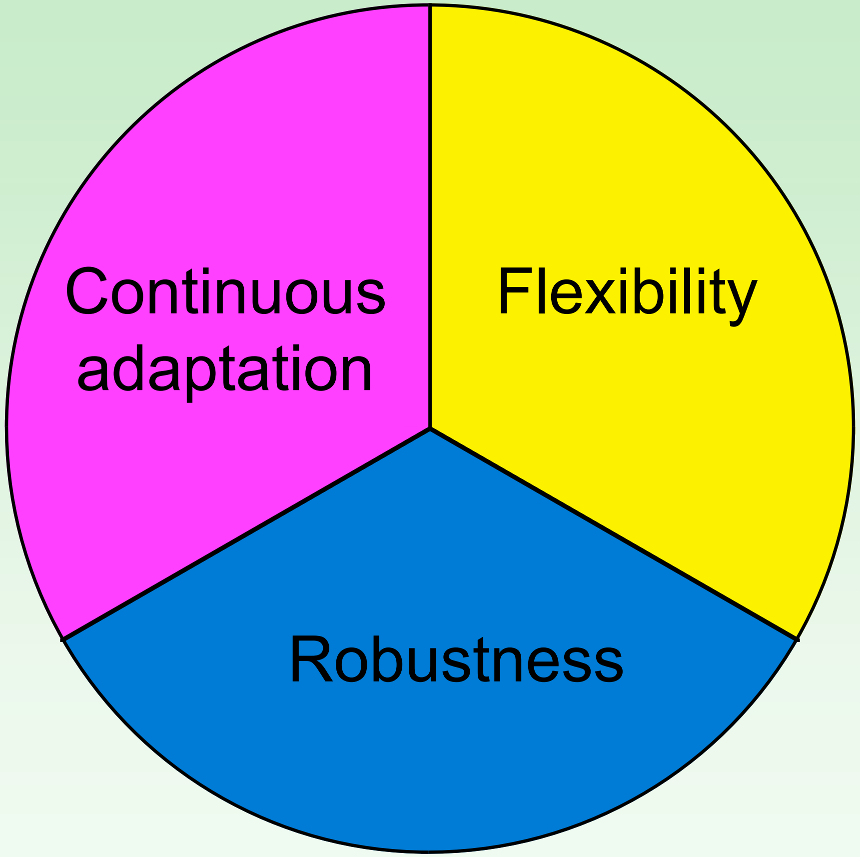
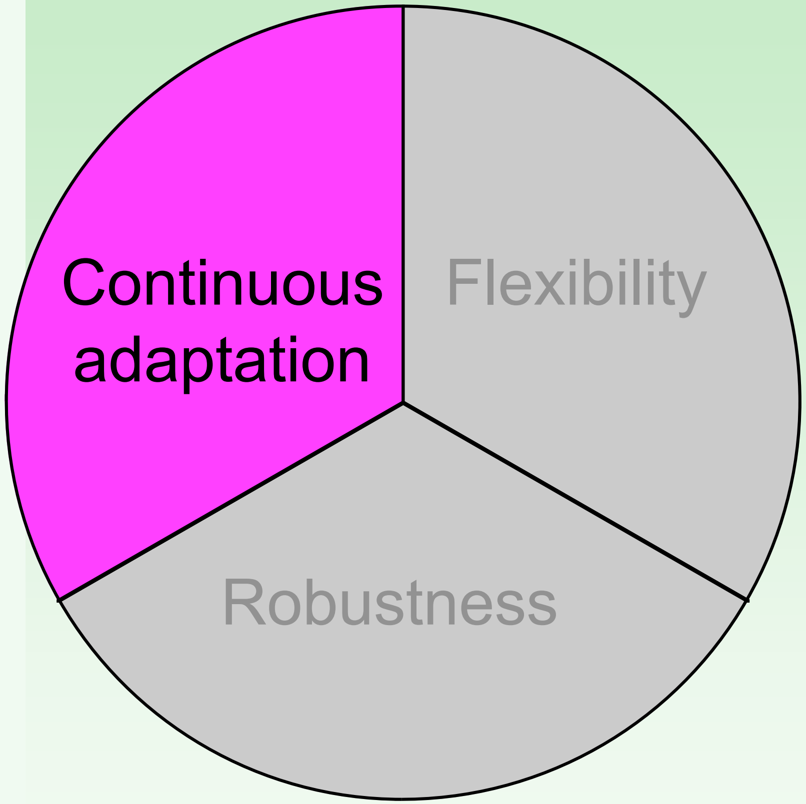
Motivation

- Many real-world applications are dynamic
  - Scheduling
  - Control problems
  - Vehicle routing
  - Portfolio optimization
  - etc.
- Current approaches
  - Ignore dynamics and re-optimize regularly
  - Use very simple control rules
- Large potential when dynamism is addressed explicitly
- Nature-inspired optimization algorithms seem particularly promising, as nature is a continuously changing environment

Three aspects in dynamic environments



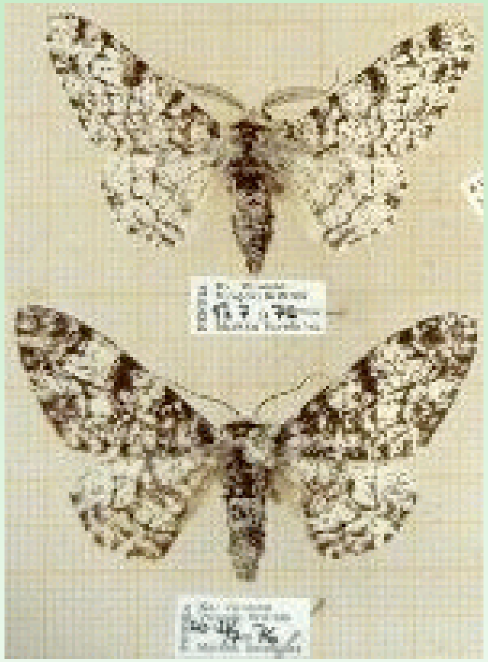
Part I - Continuous Adaptation



- The problem of convergence
- Remedies
- Benchmarks
  (in particular: Moving Peaks)
- Additional aspects
  - Learning
  - Theory
- Other metaheuristics
  - Ant Colony Optimization
  - Particle Swarm Optimization

Nature is able to adapt

Evolutionary Algorithms

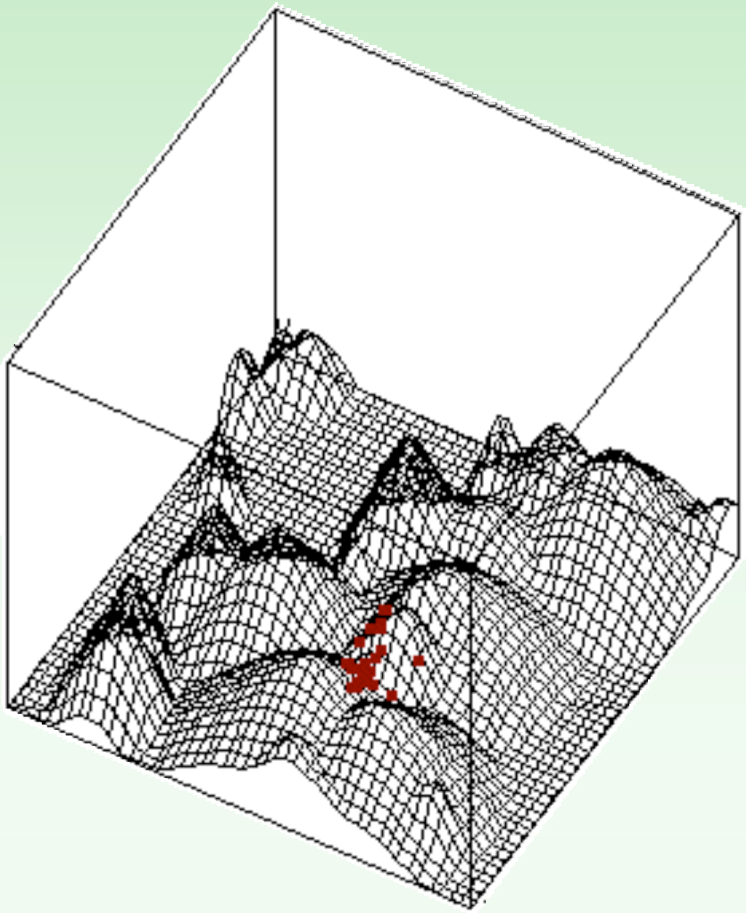


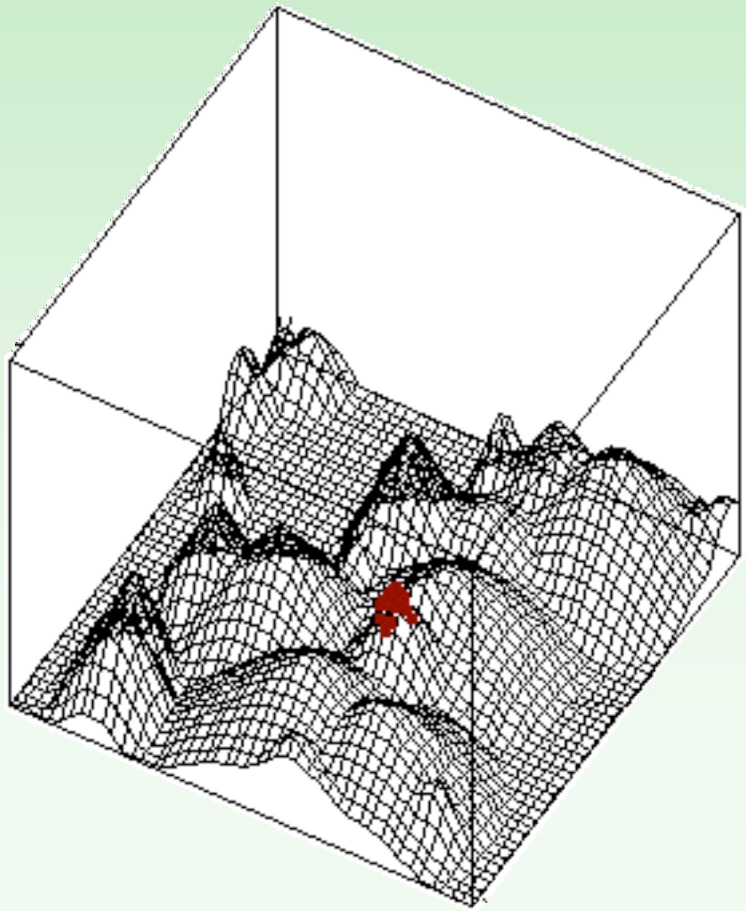
Dynamic Optimization Problems

The problem of convergence

For static optimization problems, convergence is desired.

If the problem is dynamic, convergence is dangerous.





Possible Remedies

1. Restart after a change
   (only choice if changes are too severe)

But: Too slow

2. Generate diversity after a change
   – Hypermutation [Cobb 1990]
   – Variable Local Search [Vavak et al. 1997]

But: Randomization destroys information,
only local search or similar to restart

Possible Remedies (2)

3. Maintain diversity throughout the run
   - Random Immigrants [Grefenstette 1992]
   - Sharing/Crowding [Andersen 1991, Cedeno & Vemuri 1997]
   - Thermodynamical GA [Mori et al. 1996]

But: Disturbes optimization process

4. Memory-enhanced EAs
   - Implicit memory [Goldberg & Smith 1987, Ng & Wong1995, Lewis et al. 1998]
     - Redundant genetic representation (e.g. diploid)
     - EA is free to use additional memory
   - Explicit memory [Ramsey & Grefenstette 1993, Trojanowski et al. 1997, Mori et al. 1997, Branke 1999]
     - Explicit rules which information to store in and retrieve from the memory

But: Only useful when optimum reappears at old location,
Problem of convergence remains

Possible Remedies (3)

5. Multi-Population approaches
   - Maintain different subpopulations on different peaks
     - adaptive memory
     - able to detect new optima
     - distance/similarity metric required
   - Self-Organizing Scouts [Branke et al. 2000, Branke 2001]
   - Multi-National EA [Ursem 2000]

Maintains useful diversity

Thermodynamical GA [Mori et al. 1996]

- Select next parent generation such that they are a good compromise between quality and diversity
- Select parents one by one such that the resulting (incomplete) parent generation minimizes

$$\min F = \langle E \rangle - TH$$

free energy

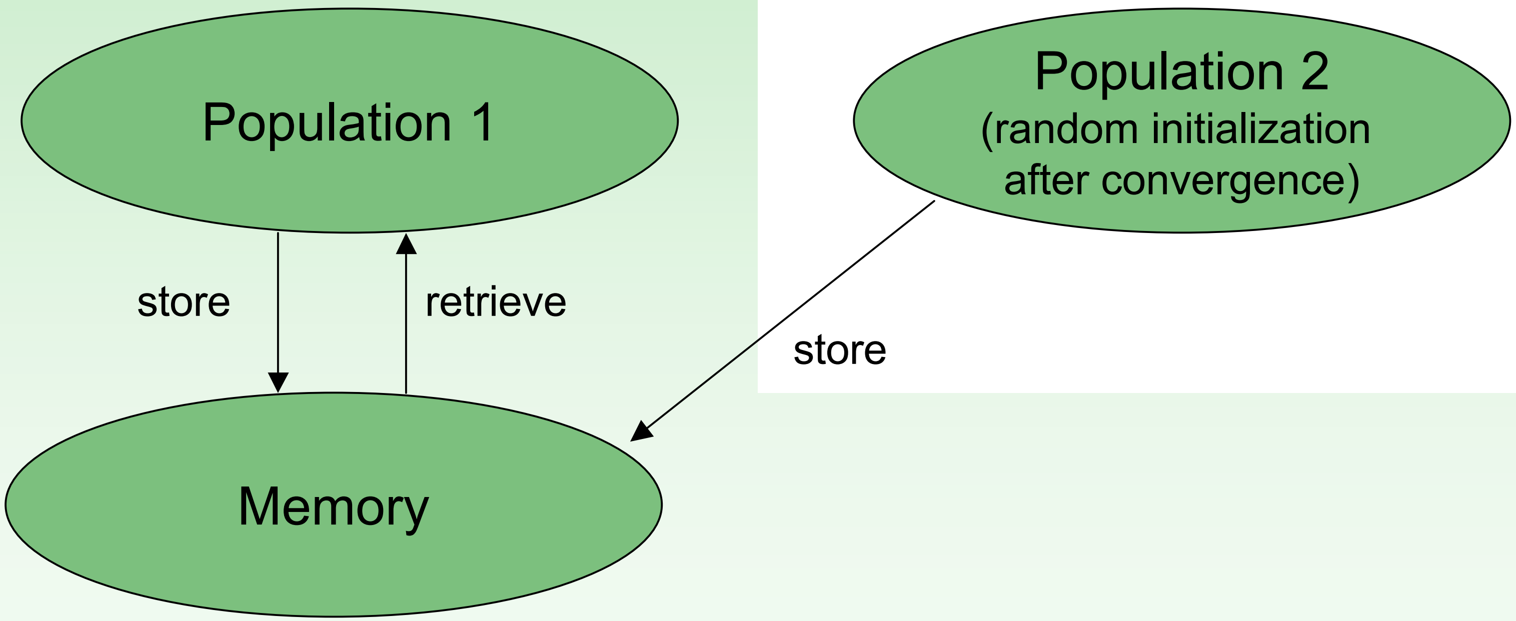
average population fitness

diversity

- Requires to tune parameter T
- Computationally expensive

Memory/Search-Approach [Branke 1999]

- Explicit memorization of individuals
- Keep the better of the two most similar



⇨ Sensible balance of exploration vs. exploitation

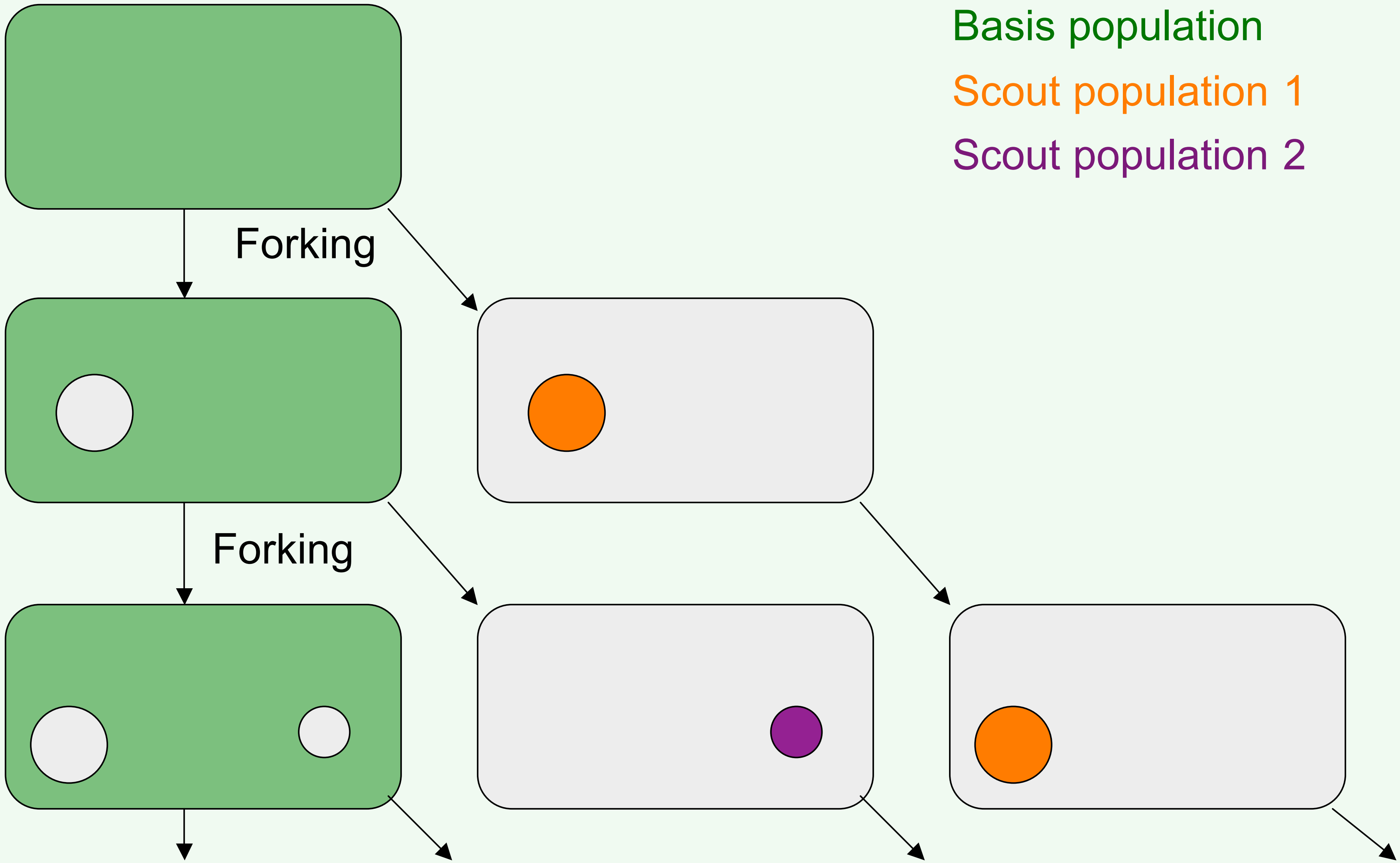
Self Organizing Scouts (SOS) [Branke 2001]

- Idea: Collect information about search space
- Whenever a local optimum has been found
  → watch it with some scouts
- Basis population should search for new peak
- Scouts should be able to track “their” peak

How does it work, really?

- When a cluster is detected in basis population
  ⇒ Forking

Forking [Tsutsui et al. 1997]



How does it work, really?

- When a cluster is detected in basis population
  ⟹ Forking
- Invalid individuals are replaced by random individuals
  ⟹ Diversification
- Best individual defines center ⟹ Tracking
- Number of individuals in scout population depends on quality and trend ⟹ Efficiency
- Size of the scout population’s search space
  - Shrinks continuously
  - Is increased when two scout populations merge

  ⟹ Adaptation

Typical benchmark problems

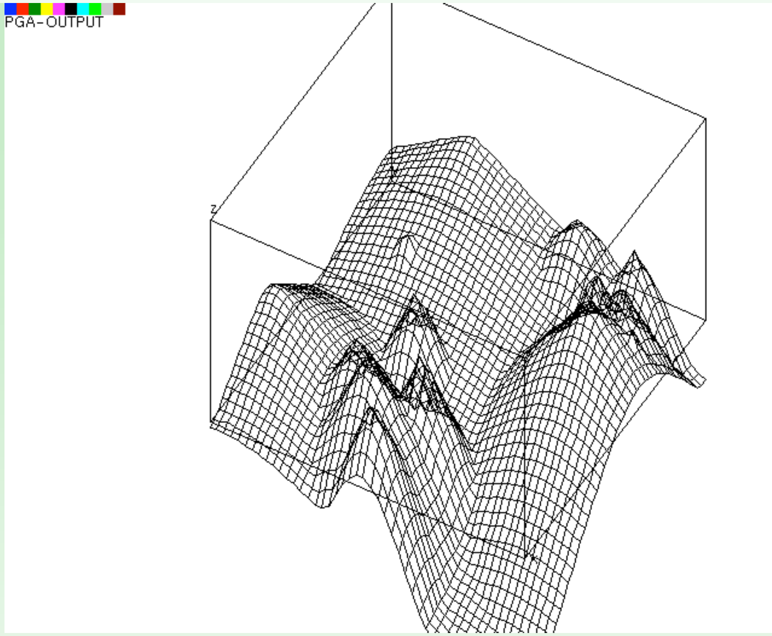
- Moving Peaks Benchmark [Branke 1999, Morrison & DeJong 1999]
- Dynamic knapsack problem, e.g. [Mori et al. 1996]
- Dynamic bit-matching, e.g. [Stanhope & Daida 1999, Droste 2003]
- Scheduling with new jobs arriving over time, e.g. [Mattfeld & Bierwirth 2004]
- Greenhouse control problem [Ursem et al. 2002]

Problem characteristics: [Branke 2001]

- Change severity
- Change frequency
- Predictability
- Cycle length / cycle accuracy

Moving peaks benchmark [Branke 1999]

available at http://www.aifb.uni-karlsruhe.de/~jbr/MovPeaks



- Multi modal environment characterised by moving peaks of varying widths and heights
- Small continuous changes in f can lead to discontinuous changes in x_{opt}
- Parameters:
  - Change frequency
  - Number of peaks
  - Severity (length of shift vector, height and width)
  - Correlation of shifts
  - Number of dimensions
  - Shape of the peaks

Performance Measure: Offline Error

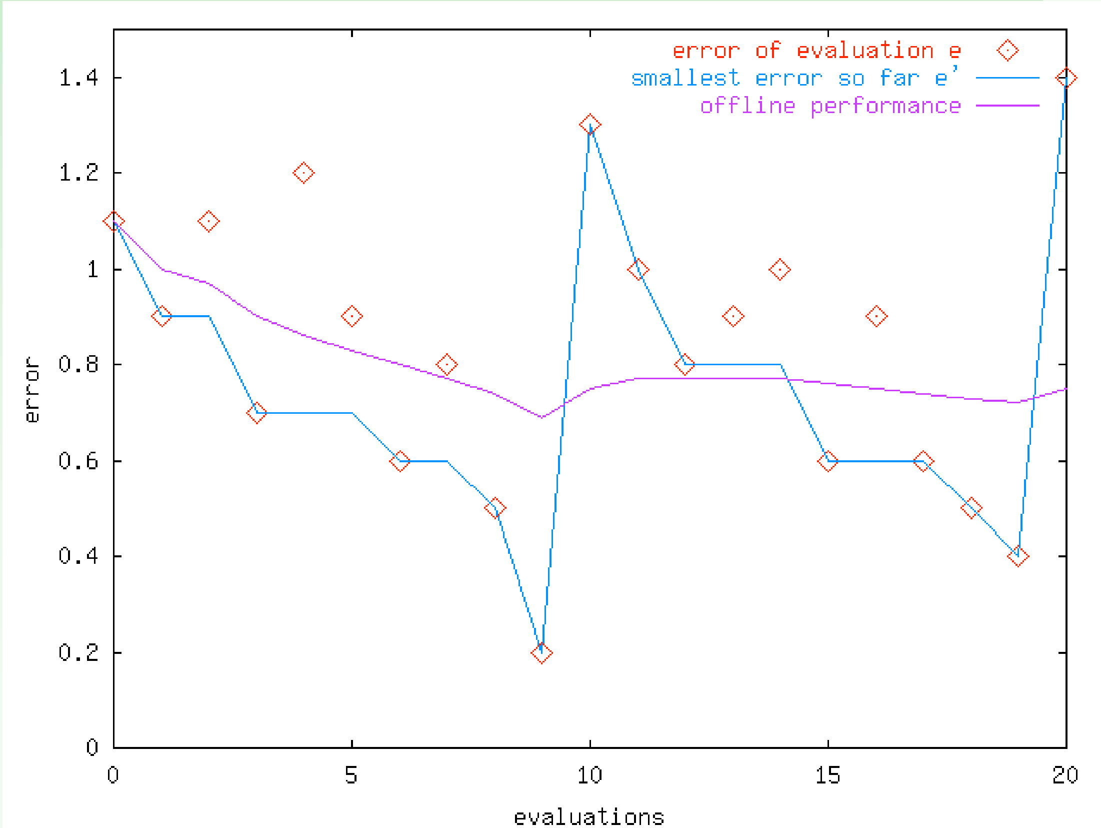
Difficulty: best solution found is not sufficient

➡ Use modified offline error $\epsilon^*(T)$

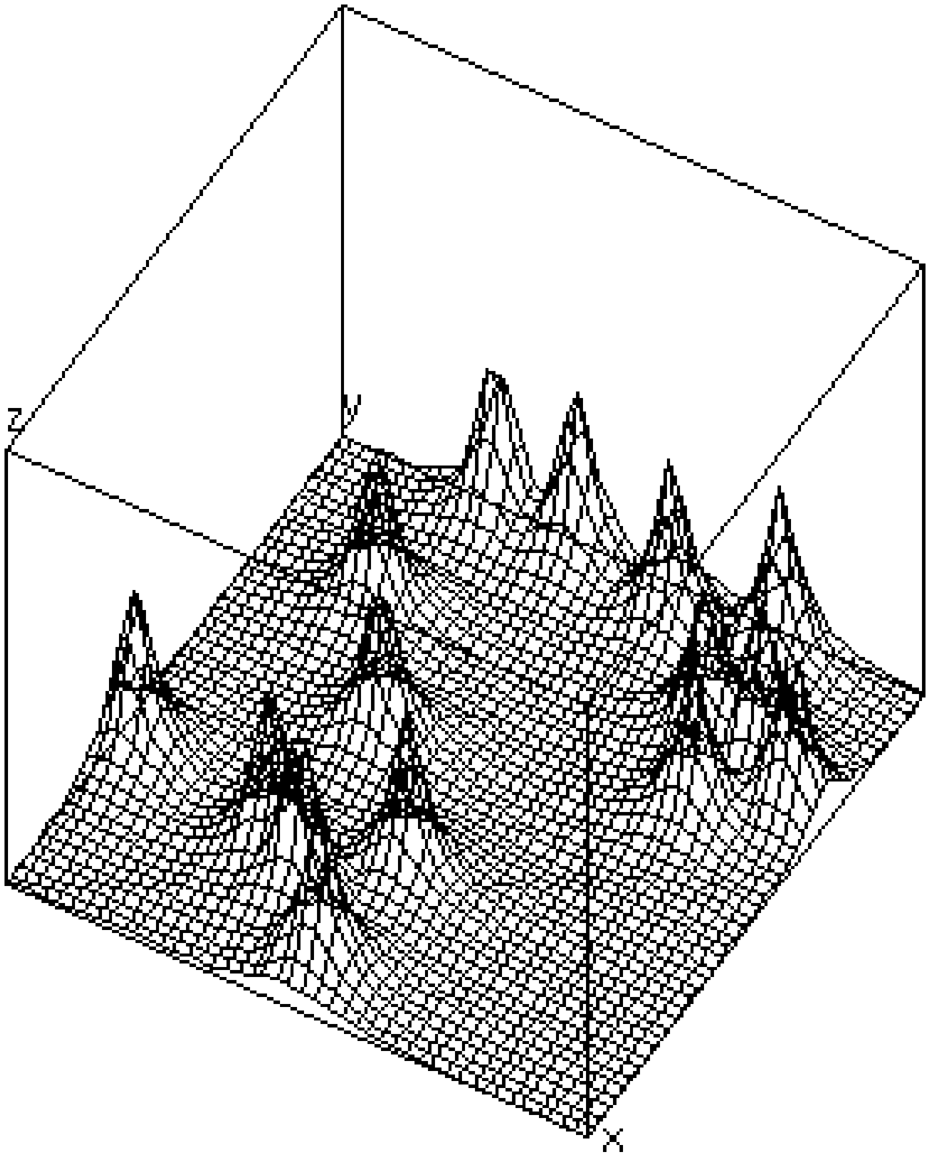
$$\epsilon^*(T) = \frac{1}{T}\sum_{t=1}^{T}(opt_t - e'_t)$$

$$e'_t = \max(e_\tau, e_{\tau+1}, \ldots, e_t)$$

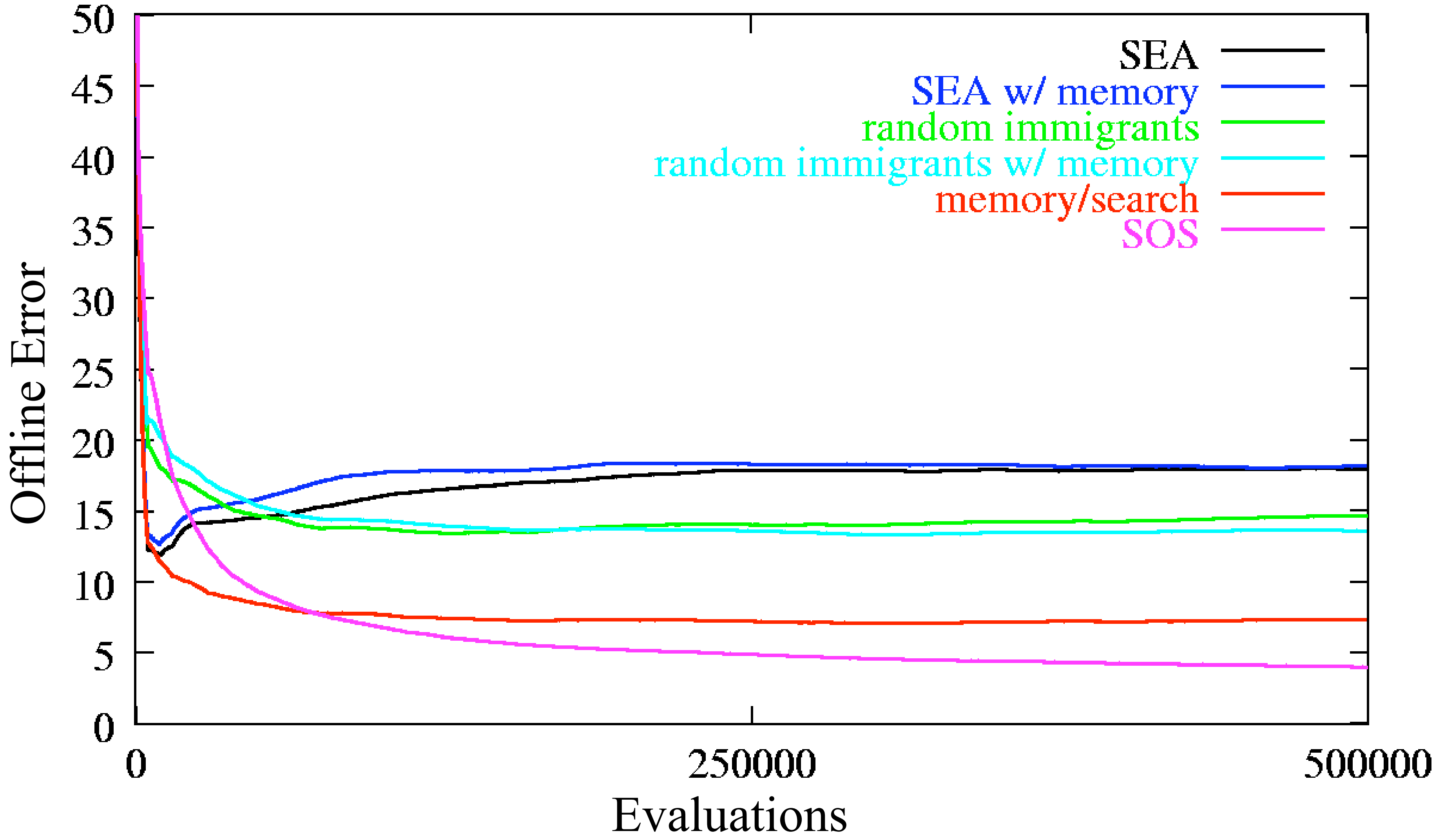
τ: time of last change



Demo: Self-Organizing Scouts

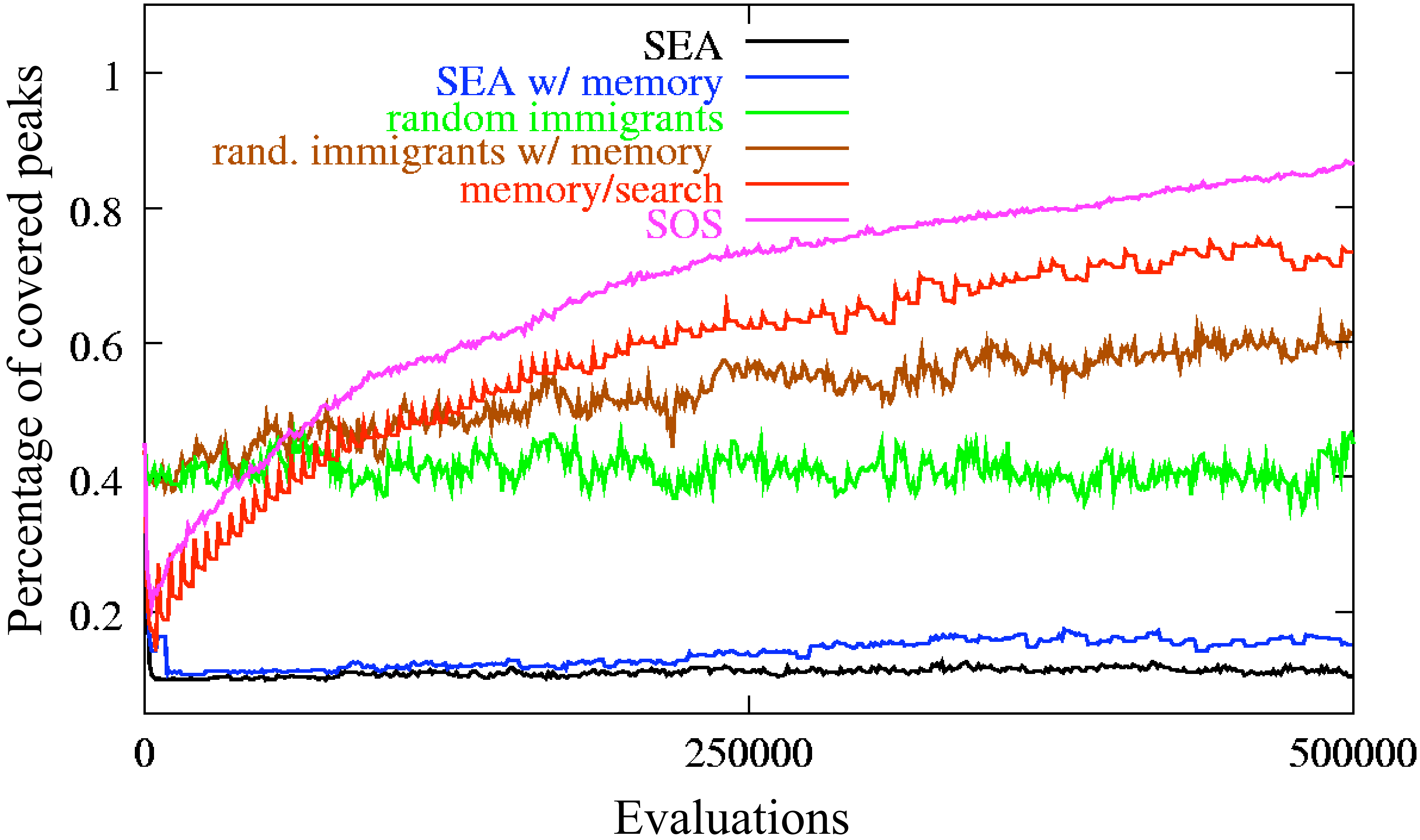


Comparison of offline error



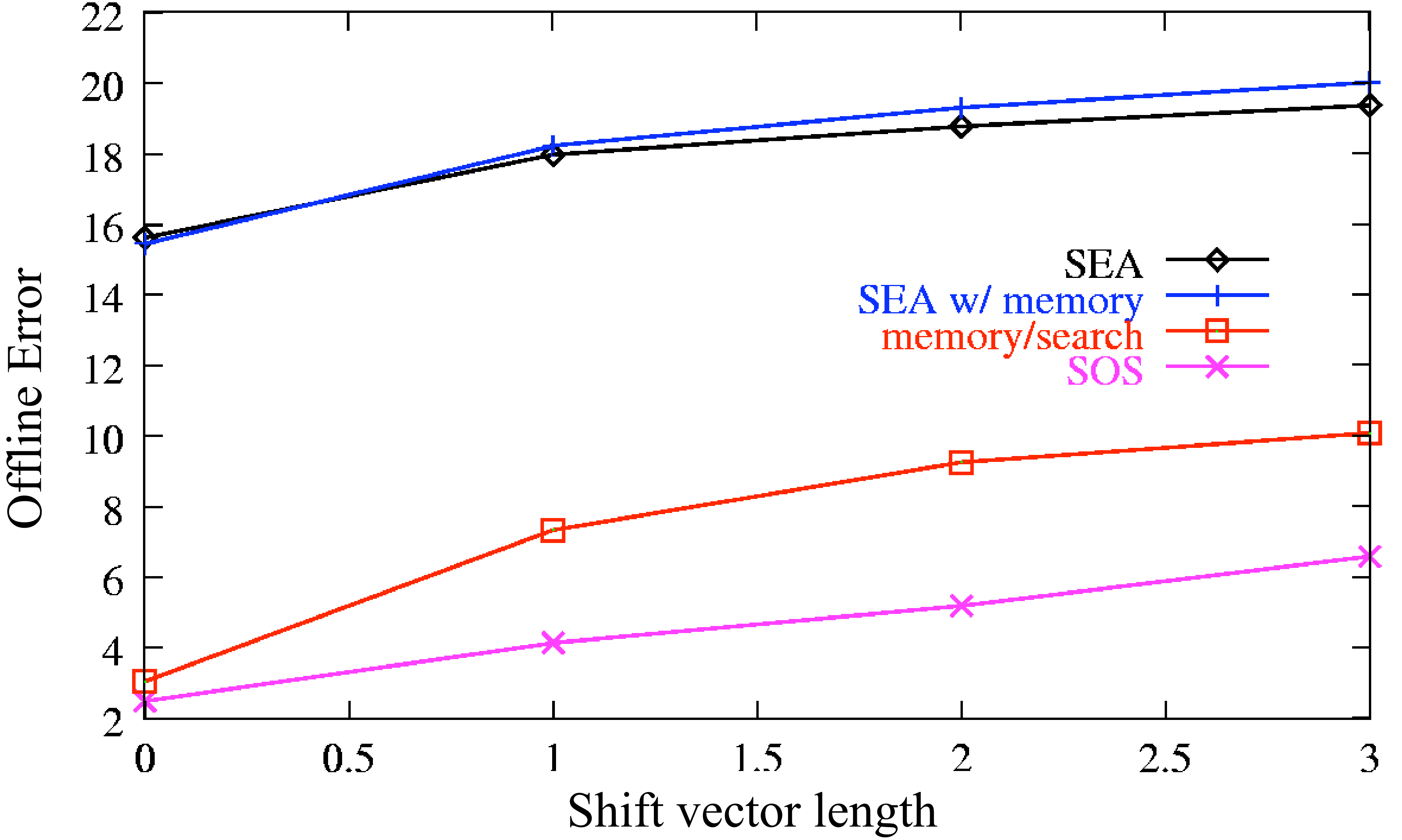
(Population size 100, 10 peaks, step size 1.0)

Percentage of covered peaks



(Population size 100, 10 peaks, step size 2.0)

Influence of step size



(After 5000 generations, 10 peaks)

Summary of Observations

- Standard EA gets stuck on single peak
- Diversity preservation slows down convergence
- Random immigrants introduce high diversity from the beginning, but benefit is limited
- Memory without diversity preservation is counterproductive
- Non-adaptive memory suffers significantly if peaks move
- Self-organizing scouts performs best

Additional Aspects: Learning of change characteristics

- If the characteristics of a change can be learned, search can be biased accordingly. Examples
  - learn severity
  - learn direction
- Is standard ES self-adaptation sufficient?
  - Perhaps not, because Gaussian mutation is not appropriate [Weicker 2003]

Additional Aspects: Learning vs. Evolution

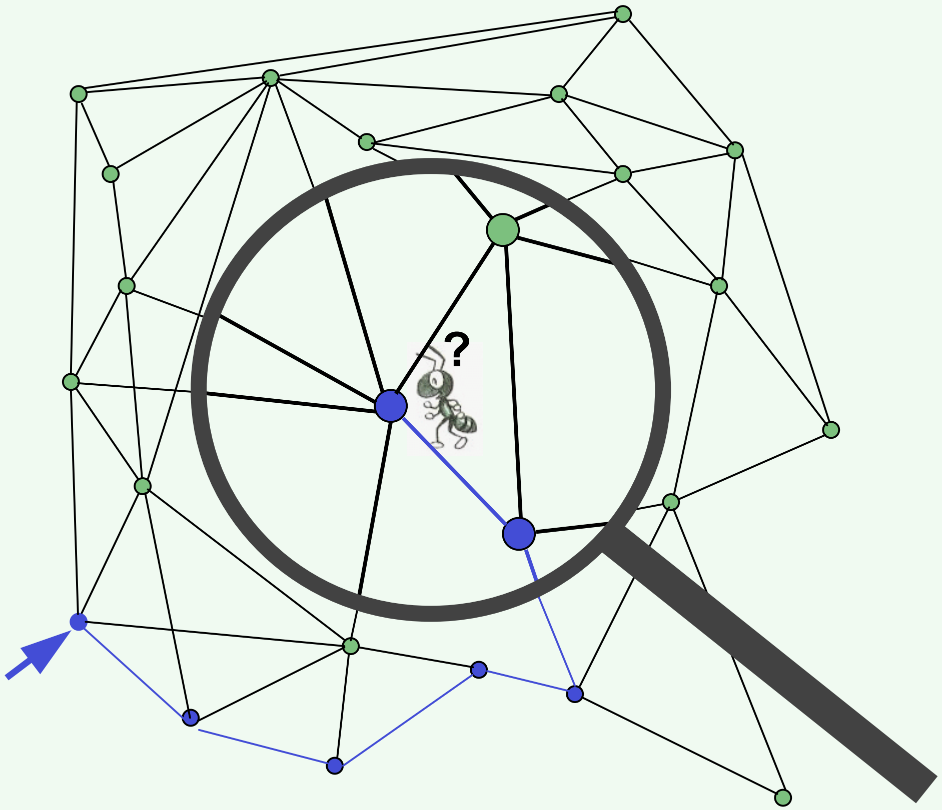
- In nature, long-term adaptation is accomplished by evolution, while short-term adaptation is achieved by learning
- Lamarckian evolution performs better in static environments, Darwinian evolution is better in dynamic environments [Sasaki & Tokoro 1999]
- Hill-climbing (learning) may be better to follow a slowly moving peak.

Additional Aspects: Theoretical Results

- (1+1) ES for the dynamic bit-matching problem [Droste 2003]
  - Maximal change severity such that runtime (first passage time) is still polynomial

- (□/□,□) ES for continuously moving sphere [Arnold/Beyer 2002]
  - Distance to optimum and mutation step size in equilibrium
  - No loss of diversity?

Other nature-inspired search heuristics: 1. Ant colony optimization (ACO)



Ants make decisions probabilistically, based on:

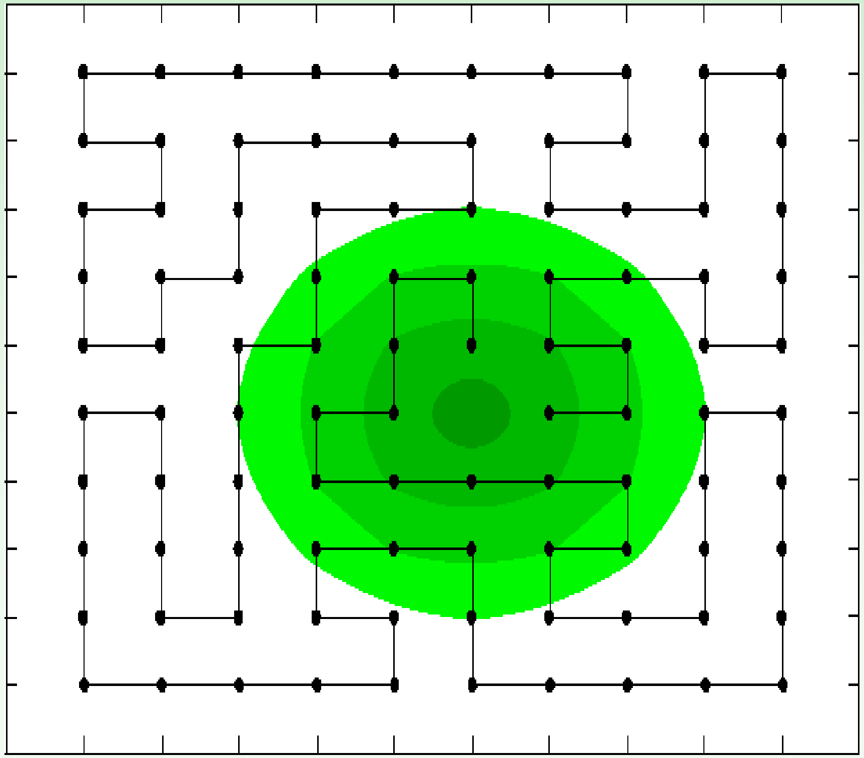
- Memory (e.g. no city may be visited twice)
- Heuristic (e.g. prefer nearby cities)
- Pheromones

In every iteration:

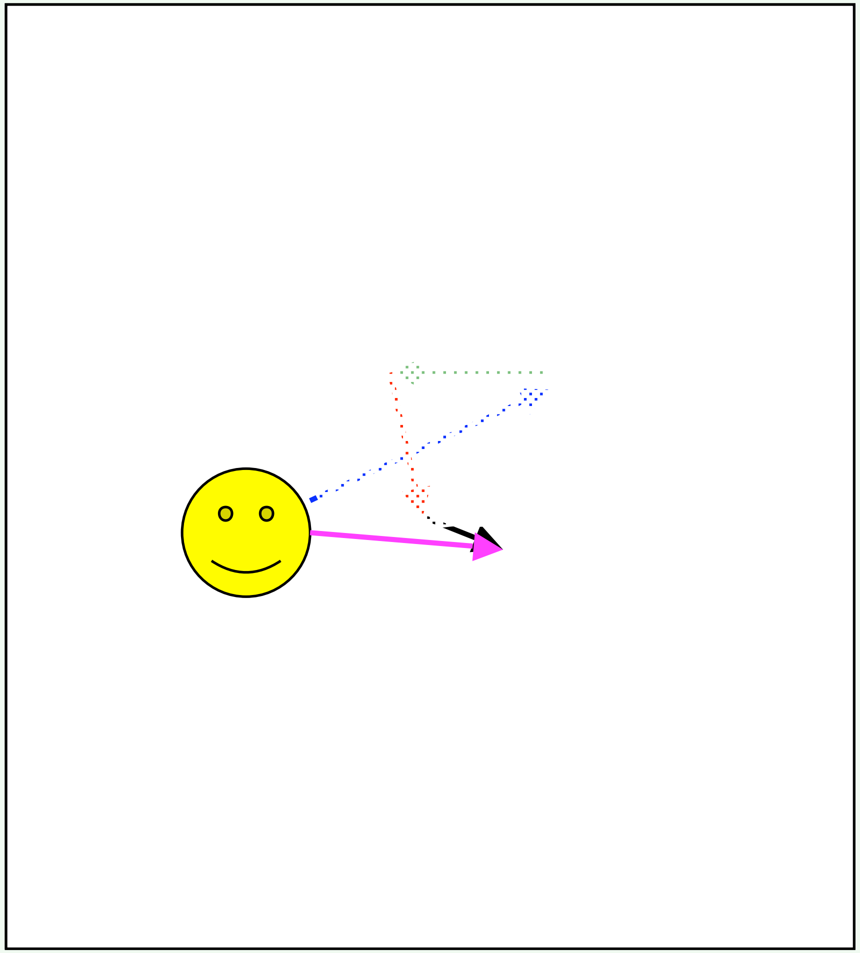
- Let m ants each construct a solution
- Ants that constructed good solutions may lay pheromone on their „decision path“
- Pheromones evaporate slowly

ACO for Dynamic Problems [Guntsch et al. 2001]

- Introduce local variance where needed
- Heuristic repair of solutions



Other nature-inspired search heuristics: 2. Particle Swarm Optimization



Swarm of particles

- Each particle
  - has velocity
  - keeps track of best visited solution
  - knows about best solution found so far

- In every iteration, each particle
  - adapts velocity, taking into account local and global best
  - moves according to new velocity
  - evaluates solution
  - updates local and global best

PSO for dynamic problems

- Re-initialization of local memory / replace with current location [Carlisle & Dozier 2000]
- Re-initialize part of the swarm population [Hu & Eberhart 2002]
- Charged particles [Blackwell & Bentley 2002]
- Hierarchical Swarms [Janson & Middendorf 2004]
- Multi Swarms [Blackwell & Branke 2004]

Memory update

Discover new peaks

Local diversity, tracking

Local diversity, tracking

Combination of ideas from
- Charged PSO
- Self-Organizing Scouts

Charged PSO

- Some of the particles are “charged”, i.e. repel each other
- Charged particles orbit nucleus similar to atom
- Neutral particles *exploit* and the charged particles *explore*
- Diversity is maintained and tracking is possible

But: difficult to control, N^2 complexity

Quantum PSO

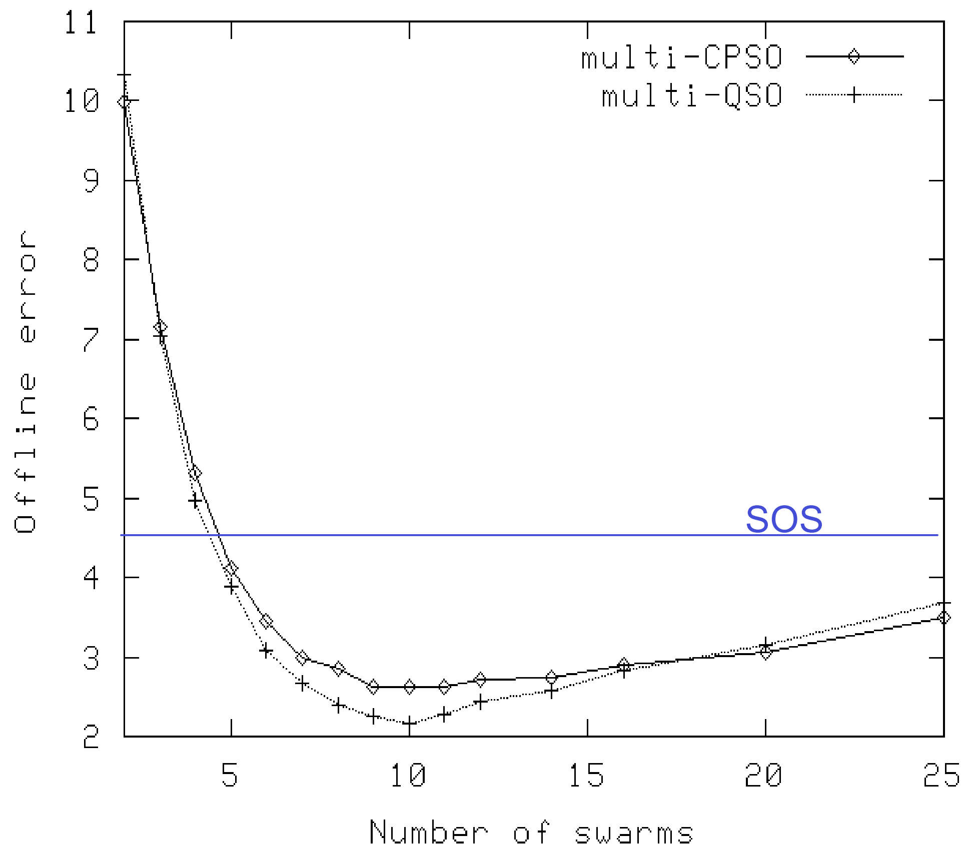
- Quantum particles are randomized within a ball of radius r_{cloud} centered on the p_g

Multi-Swarms

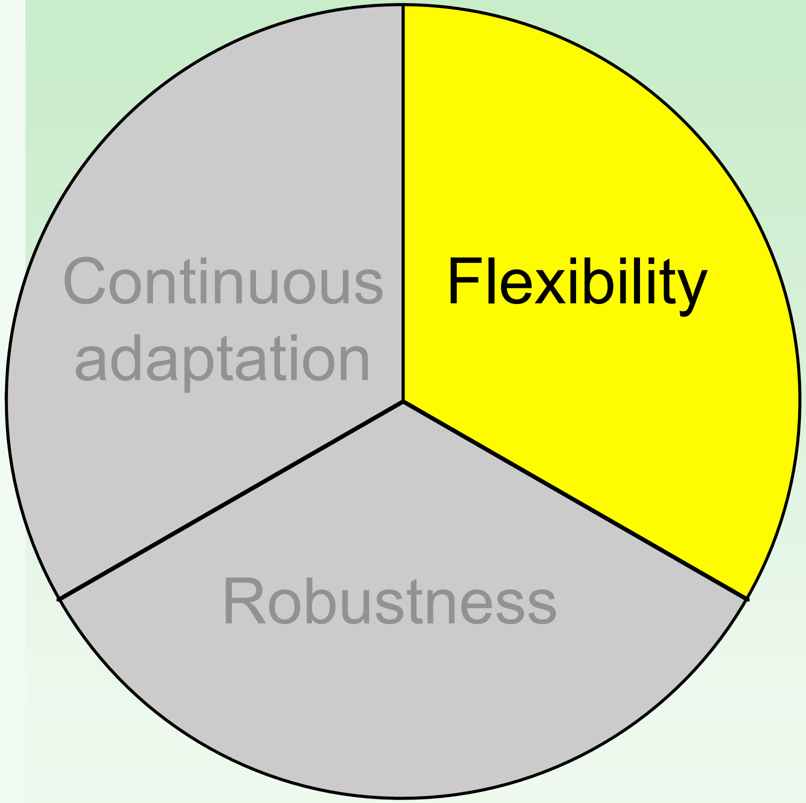
- More than one swarm
- Charged or quantum particles to allow tracking of peak
- Exclusion:
  - If global best of two swarms become too similar: competition
  - Swarm with lower fitness is randomized
  - Winner may continue optimization

Results

- Single swarms (PSO, CPSO and QSO) are similar, and close to single population EA result
- QSO generally better than CPSO
- Best result for M = number of peaks
- Better than SOS for 5 ≤ M ≤ 25



Part II: Flexibility



- Motivation
- Challenges
- Example:

  Job shop scheduling

General idea

- Be prepared!
- Be flexible!

„If a problem requires sequential decision making under an uncertain future, and if the decisions impact the future state of the system, decision making should anticipate future needs. This means that an optimization algorithm should not just focus on the primary objective function, but should additionally try to move the system into a flexible state, i.e. a state that facilitates adaptation if necessary.“ [Branke&Mattfeld, to appear]

- Flexibility as secondary objective
- Easy to integrate into black box optimization heuristics

Intuitive examples

- Portfolio optimization:
  Don‘t invest all your money long-term
- Transportation:
  Drive a route where additional customers are expeced
- Manufacturing:
  Buy machines that can produce different products

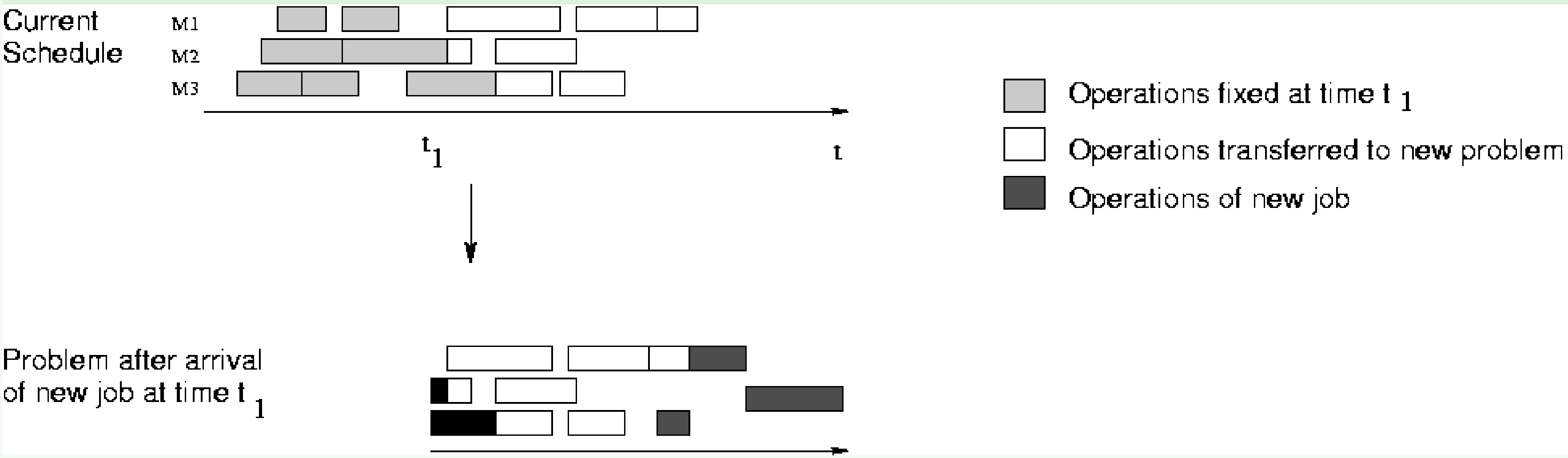
Challenges:

1. What constitutes flexibility in the specific context?
2. How to integrate flexibility goal into the algorithm?

Example:
Minimum summed tardiness scheduling

Problem:

- New jobs arrive dynamically and have to be integrated into the schedule
- Execute current best schedule until change occurs
- see [Branke & Mattfeld 2000]



What makes a schedule flexible?

- Flexibility = available machine capacity later in the schedule
- Secondary objective: avoid early idle time, penalty on idle time, linearly decreasing up to time τ

Integration into EA:

- Tardiness and idle time penalty normalized w.r.t. population max and min
- Fitness = linear combination of tardiness and idle time penalty

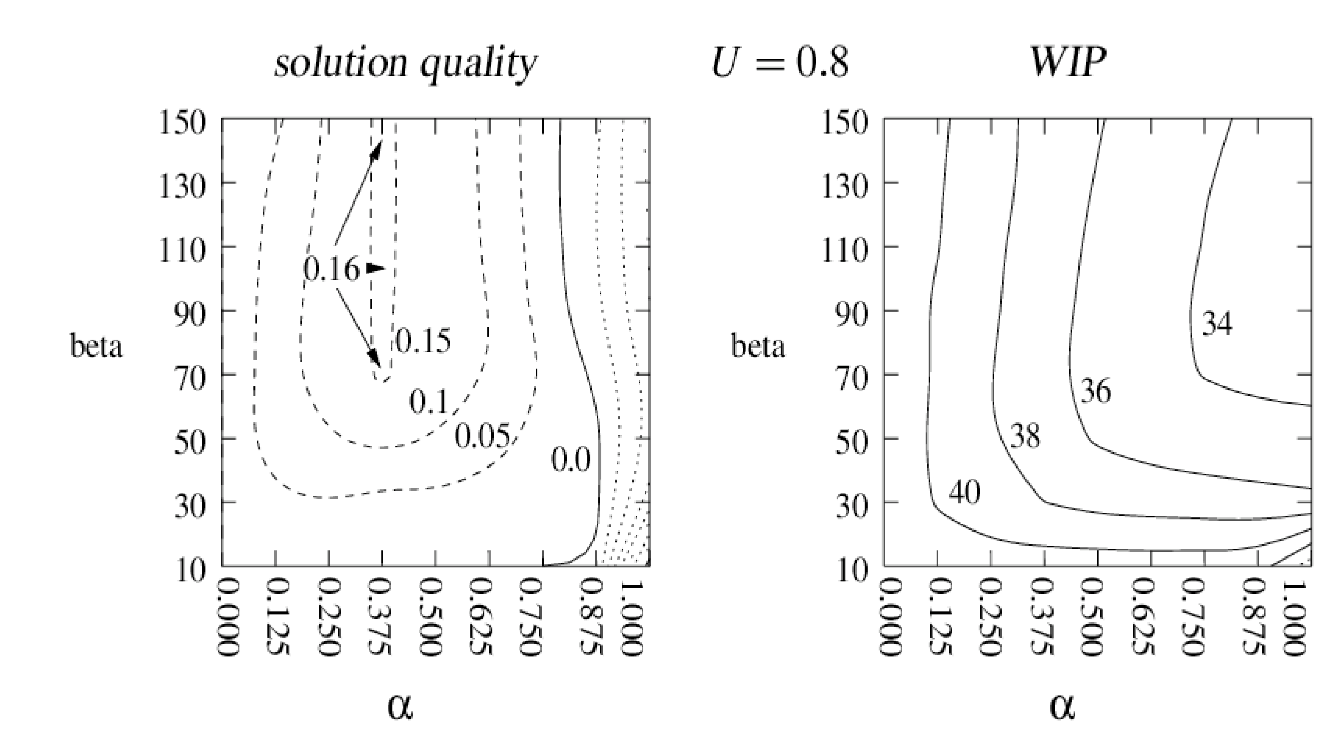
$$f_k = (1 - \alpha)\hat{T} + \alpha\hat{P}$$

$$\hat{T} = \frac{T_k - \min\{T_m\}}{\max\{T_m\} - \min\{T_m\}}$$

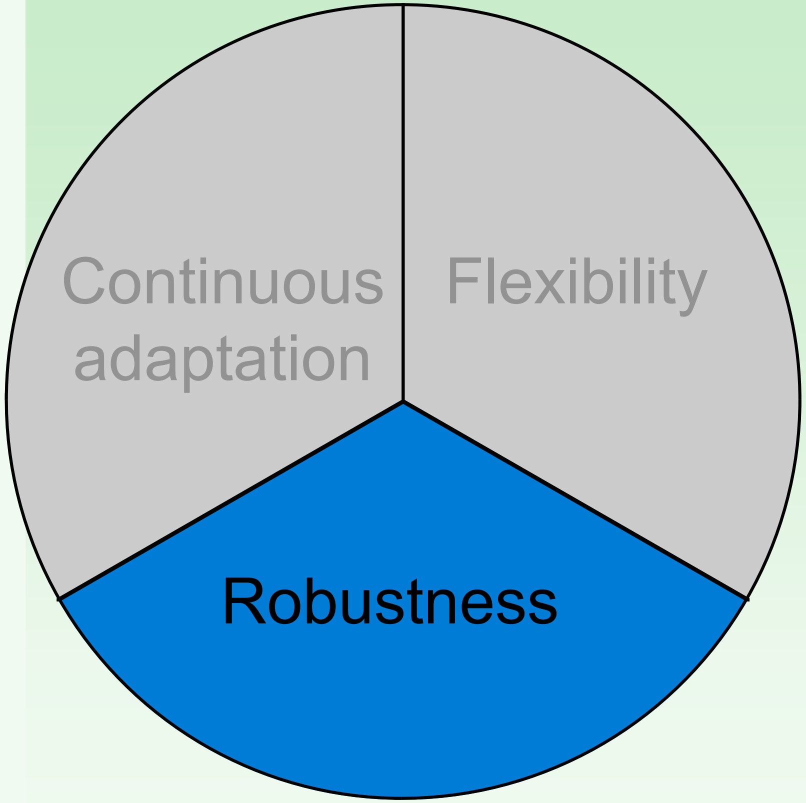
$$\hat{P} = \frac{P_k - \min\{P_m\}}{\max\{P_m\} - \min\{P_m\}}$$

Result

- Reduction in tardiness objective:
  - Evolutionary algorithm: 14-22%
  - Biased random sampling: 15-18%
- Improvement relatively independent of parameter setting



Part III: Robustness



- Robustness against
  - environmental changes
  - implementation noise
- Estimating the effective fitness
- Trade-off between fitness and robustness

Two Variants

1. Environment changes, but adaptation is not possible
   - Environment changes too quickly
   - Adaptation too expensive
   - Adaptation technically impossible
   - Commitment long term

   Solution needs to have high quality even if environment changes
2. Implementation of solution is prone to errors
   - Manufacturing tolerances
   - Growth processes

   Solution has to have high quality even if modified slightly

Both variants can be treated the same way.

Effective Fitness

- Given: probability distribution over different scenarios / deviations
- Goal (*effective* fitness):
  - optimize expected value
  - optimize worst case
  - ...

$$x \longrightarrow x + \delta$$

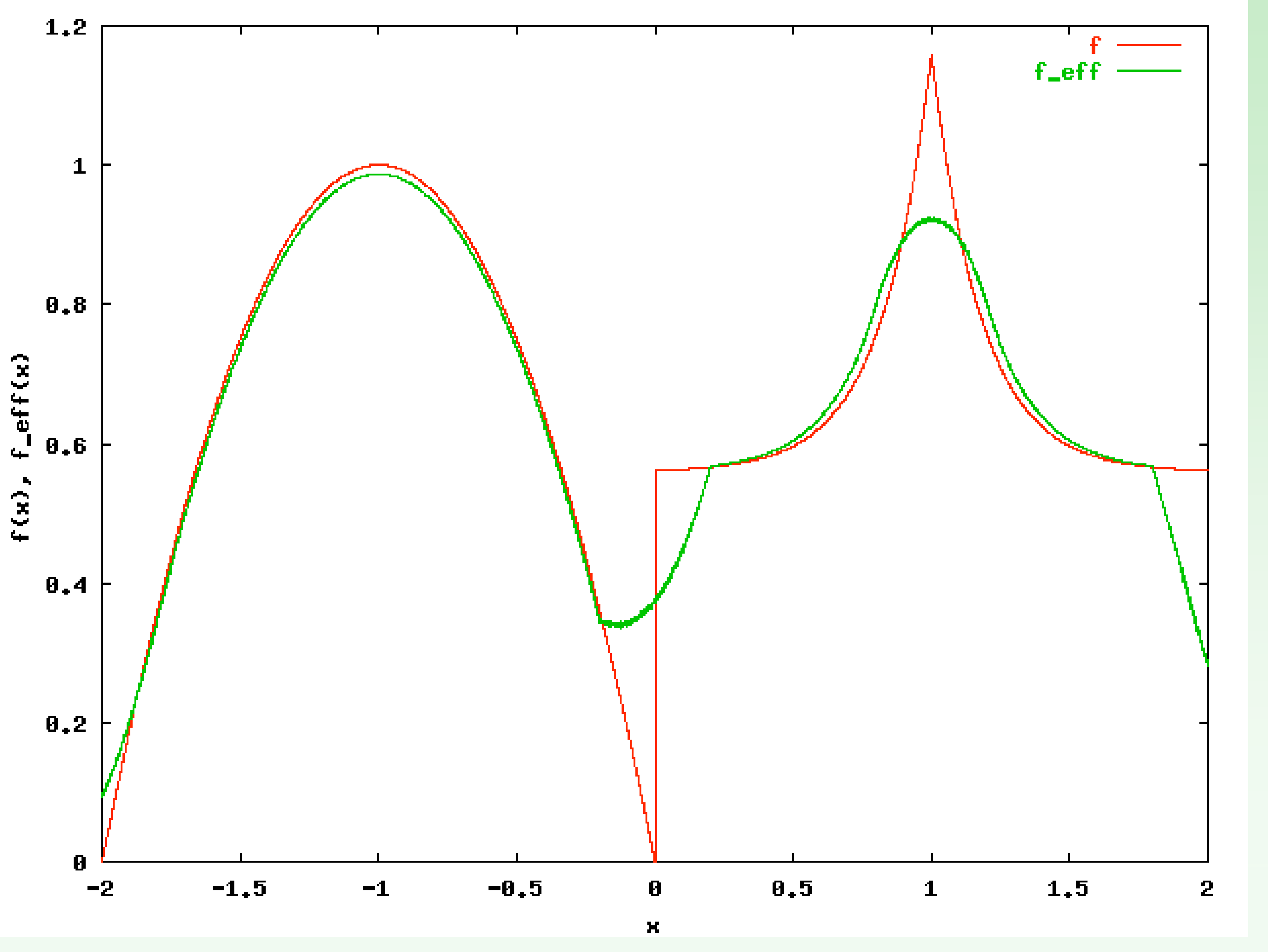
$$f(x) \rightarrow f_{eff}(x) = E(f(x+\delta)) = \int_{\delta} f(x+\delta)\, p(\delta)\, d\delta$$

$p(\delta)$: probability density function of δ

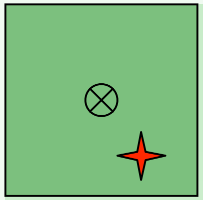
- Effective fitness can be determined by Monte-Carlo integration

Effective Fitness - Example [Branke 2001]

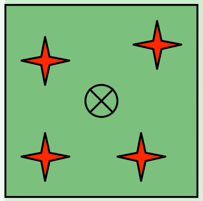
δ gleichverteilt in $[-0.2,\ldots,0.2]$



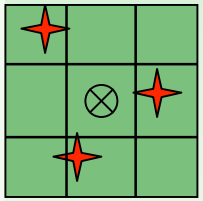
Efficiently estimating expected values



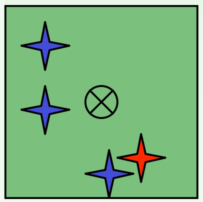
Simply disturb individuals [Tsutsui & Ghosh 1997]



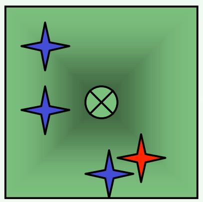
Multiple samples [Branke 1998]



Latin hypercube sampling
[Loughlin &Ranjithan 1999, Branke 2001b]



Use history of search [Branke 1998]



Use approximation models

Trade-off between solution quality and robustness

- Variance as second objective
- Evolutionary multi-objective optimization
- [Sendhoff & Jin 2000]

Conclusion Part I-III

- Very interesting and active research area
- Still in its infancy
- Nature inspired optimization has a lot to offer
  - Continuous adaptation
  - Multi-objective optimization
    - Flexibility
    - Robustness
    - Change-cost
  - Ability to cope with noise
    - Multiple sampling of promising areas
    - Population information may be used

Further readings

- EvoDOP repository and mailinglist
  http://www.aifb.uni-karlsruhe.de/~jbr/EvoDOP
- Workshop on Evolutionary Optimization in Stochastic and Dynamic Environments (EvoSTOC)
- Books:
  - J. Branke: „Evolutionary Optimization in Dynamic Environments“, Kluwer, 2001
  - K. Weicker: „Evolutionary Algorithms and Dynamic Optimization Problems“, Der Andere Verlag, 2003
- Journals:
  - Soft Computing Journal, special issue on dynamic optimization problems (to appear)
  - IEEE Transactions on Evolutionary Computation, special issue on optimization in uncertain environments (to appear)

References

[Andersen 1991] H. C. Andersen. An investigation into genetic algorithms, and the relationship between speciation and the tracking of optima in dynamic functions. Honours thesis, Queensland University of Technology, Brisbane, Australia

[Arnold& Beyer 2002] D. V. Arnold and H.-G. Beyer. Random Dynamics Optimum Tracking with Evolution Strategies. In J.J. Merelo, P. Adamidis, H.-G. Beyer, J.L. Fernández-Villacañas, and H.-P. Schwefel, editors, *Parallel Problem Solving from Nature*, pages 3-12, Springer.

[Blackwell & Bentley 2002] T. M. Blackwell, and P. J. Bentley, P.J.: Dynamic search with charged swarms. *Genetic and Evolutionary Computation Conference*, pages 19-26

[Blackwell & Branke 2004] T. M. Blackwell, and J. Branke. Multi-swarm optimization in dynamic environments. In: G. Raidl et al. (eds), Applications of Evolutionary Computing. Springer, LNCS 3005, pages 489-500

[Branke 1999] J. Branke. Memory enhanced evolutionary algorithms for changing optimization problems. In *Congress on Evolutionary Computation CEC99* , Volume 3, pages 1875-1882. IEEE

[Branke et al. 2000] J. Branke, T. Kaußler, C. Schmidt, and H. Schmeck. A multi-population approach to dynamic optimization problems. In *Adaptive Computing in Design and Manufacturing*. Springer

[Branke 2001] J. Branke. *Evolutionary Optimization in Dynamic Environments*.Kluwer

[Branke 2001b] J. Branke. Reducing the sampling variance when searching for robust solutions. In: *Genetic and Evolutionary Computation Conference*, L. Spector et al. (eds.), Morgan Kaufmann, pages 235-242

[Branke & Mattfeld 2000] J. Branke and D. Mattfeld. Anticipation in dynamic optimization: The scheduling case. In: *Parallel Problem Solving from Nature*, Springer, pages 253-262

[Carlisle & Dozier 2000] Carlisle, A. and Dozier, G.: Adapting Particle Swarm Optimization to Dynamic Environments. *Int. Conference on Artificial Intelligence*. pages 429-434

[Cedeno & Vemuri 1997] W. Cedeno and V. R. Vemuri. On the use of niching for dynamic landscapes. In *International Conference on Evolutionary Computation* . IEEE.

[Cobb 1990] H. G. Cobb. An investigation into the use of hypermutation as an adaptive operator in genetic algorithms having continuouis, time-dependent nonstationary environments. Technical Report AIC-90-001, Naval Research Laboratory, Washington, USA.

[Droste 2003] S. Droste. Analysis of the (1+1) EA for a dynamically bitwise changing OneMax. In E. Cantu-Paz, editor, *Genetic and Evolutionary Computation Conference*, volume 2723 of *LNCS* , pages 909-921. Springer

[Goldberg & Smith 1987] D. E. Goldberg and R. E. Smith. Nonstationary function optimization using genetic algorithms with dominance and diploidy. In J. J. Grefenstette, editor, *Second International Conference on Genetic Algorithms* , pages 59-68. Lawrence Erlbaum Associates, 1987

[Grefenstette 1992] J. Grefenstette. Genetic algorithms for changing environments. In R. Maenner and B. Manderick, editors, *Parallel Problem Solving from Nature 2* , pages 137-144. North Holland

[Guntsch et al. 2001] M. Guntsch, M. Middendorf, and H. Schmeck: An Ant Colony Optimization Approach to Dynamic TSP. In: L. Spector et al. (eds.) *Genetic and Evolutionary Computation Conference*, San Francisco, CA: Morgan Kaufmann pages 860-867.

[Hu & Eberhart 2002] X. Hu, and R. C. Eberhart. Adaptive particle swarm optimisation: detection and response to dynamic systems. *Congress on Evolutionary Computation*. Pages 1666-1670

[Janson & Middendorf 2004] T. S. Janson and M. Middendorf. A hierarchical particle swarm optimizer for dynamic optimization problems. In: G. Raidl et al. (eds), Applications of Evolutionary Computing. Springer, LNCS 3005, pages 513-524

[Jin & Sendhoff 2003]Y. Jin and B. Sendhoff. Trade-off between optimality and robustness: An evolutionary multiobjective approach. In: Intl. Conference on Evolutionary Multi-criterition Optimization, LNCS 2632, Springer, pages 237-251

[Lewis et al. 1998] J. Lewis, E. Hart, and G. Ritchie. A comparison of dominance mechanisms and simple mutation on non-stationary problems. In A. E. Eiben, T. Bäck, M. Schoenauer, and H.-P. Schwefel, editors, *Parallel Problem Solving from Nature* , number 1498 in LNCS, pages 139-148. Springer, 1998.

[Loughlin &Ranjithan 1999] D. H. Loughlin and S. Ranjithan. Chance-constrained genetic algorithms. In: Banzhaf et al. (eds.), *Genetic and Evolutionary Computation Conference*, Morgan Kaufmann, pages 369-376

[Mattfeld & Bierwirth 2004] D. C. Mattfeld and C. Bierwirth. An efficient genetic algorithm for job shop scheduling with tardiness objectives. *European Journal of Operational Research* 155(3), pages 616-630

[Mori et al. 1996] N. Mori, H. Kita, and Y. Nishikawa. Adaptation to a changing environment by means of the thermodynamical genetic algorithm. In H.-M. Voigt, editor, *Parallel Problem Solving from Nature* , number 1141 in LNCS, pages 513-522. Springer Verlag Berlin

[Mori et al. 1997] N. Mori, S. Imanishi, H. Kita, and Y. Nishikawa. Adaptation to changing environments by means of the memory based thermodynamical genetic algorithm. In T. Bäck, editor, *Seventh International Conference on Genetic Algorithms* , pages 299-306. Morgan Kaufmann.

[Morrison & DeJong 1999] R. W. Morrison and K. A. DeJong. A test problem generator for non-stationary environments. In *Congress on Evolutionary Computation*, volume 3, pages 2047-2053. IEEE

[Ng & Wong 1995] K. P. Ng and K. C. Wong. A new diploid scheme and dominance change mechanism for non-stationary function optimization. In *Sixth International Conference on Genetic Algorithms* , pages 159-166. Morgan Kaufmann,

[Ramsey & Grefenstette 1993] C. L. Ramsey and J. J. Grefenstette. Case-based initialization of genetic algorithms. In S. Forrest, editor, *Fifth International Conference on Genetic Algorithms* , pages 84-91. Morgan Kaufmann.

[Sasaki & Tokoro 1999] T. Sasaki and M. Tokoro. Evolving learnable neural networks under changing environments with various rates of inheritance of acquired characters: Comparison between darwinian and lamarckian evolution. *Artificial Life* , 5(3):203-223

[Stanhope & Daida 1999] S. A. Stanhope and J. M. Daida. Genetic algorithm fitness dynamics in a changing environment. In *Congress on Evolutionary Computation*, volume 3, pages 1851-1858. IEEE

[Tsutsui & Ghosh 1997] S. Tsutsui and A. Ghosh. Genetic algorithms with a robust solution searching scheme. *IEEE Transactions on Evolutionary Computation* 1(3): 201-208

[Tsutsui et al. 1997] S. Tsutsui, Y. Fjimoto, and A. Ghosh. Forking genetic algorithms: Gas with serach space division schemes. *Evolutionary Computation* 5(1), pages 61-80

[Trojanowski et al. 1997] K. Trojanowski, Z. Michalewicz, and Jing Xiao. Adding memory to the evolutionary planner/navigator. In *IEEE Intl. Conference on Evolutionary Computation*, pages 483-487.

[Ursem 2000] R. K. Ursem. Multinational GA optimization techniques in dynamic environments. In D. Whitley, D. Goldberg, E. Cantu-Paz, L. Spector, I. Parmee, and H.-G. Beyer, editors, *Genetic and Evolutionary Computation Conference* , pages 19-26. Morgan Kaufmann

[Ursem et al. 2002] R. K. Ursem, T. Krink, M.T. Jensen, and Z. Michalewicz: Analysis and modeling of control tasks in dynamic systems. In: IEEE Transactions on Evolutionary Computation, 6(4), Pates 378-389

[Vavak et al. 1997] F. Vavak, K. Jukes, and T. C. Fogarty. Adaptive combustion balancing in multiple burner boiler using a genetic algorithm with variable range of local search. In T. Bäck, editor, *Seventh International Conference on Genetic Algorithms* , pages 719-726. Morgan Kaufmann.

[Weicker 2003] K. Weicker: „Evolutionary Algorithms and Dynamic Optimization Problems“, Der Andere Verlag

Questions

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