A Hierarchical Evolutionary Approach to Multi-Objective Optimization

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- Based on the SEAMO algorithm (a simple evolutionary algorithm for multi-objective optimization)
- A better spread of solutions are obtained if subpopulations of various sizes are used
- Three alternative hierarchical models are tried and the results compared

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Premature convergence is a serious problem with EAs, and is encountered with single and multi-objective problems alike.

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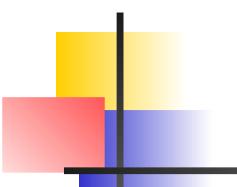
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- They are particularly simple to implement
- No complex global calculations are required for fitness or dominance



Test problems

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Multiple knapsack problems (MKPs)

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- Continuous functions, SPH-2, ZDT6, QV and KUR



The SEAMO Framework

Procedure **SEAMO**

Begin

Generate N random individuals {N is the population size}

Evaluate the objective vector for each population member and store it

Repeat

For each member of the population

This individual becomes the first parent

Select a second parent at random

Apply crossover to produce single offspring

Apply a single mutation to the offspring

Evaluate the objective vector produced by the offspring

if offspring qualifies

Then the offspring replaces a member of the population else it dies

Endfor

Until stopping condition satisfied

Print all non-dominated solutions in the final population

End

Replacement Strategy for SEAMO2

- 1. if offspring harbors a new best-so-far Pareto component
 - (a) it replaces a parent, if possible
 - (b) **else** it replaces another individual at random
- 2. else if offspring dominates either parent it replaces it
- 3. **else if** offspring is neither dominated by nor dominates either parent it replaces another individual that it dominates at random
- 4. otherwise it dies

Note: phenotypic duplicates are deleted





Order-based representation with a first fit decoder



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- Cycle Crossover (CX)



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- A simple mutation operator swaps two arbitrarily selected objects within a single permutation list

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One-point crossover

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- One-point crossover
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- Deletion of duplicates: component objective functions x_i and x'_i of x and x', are equal if and only if

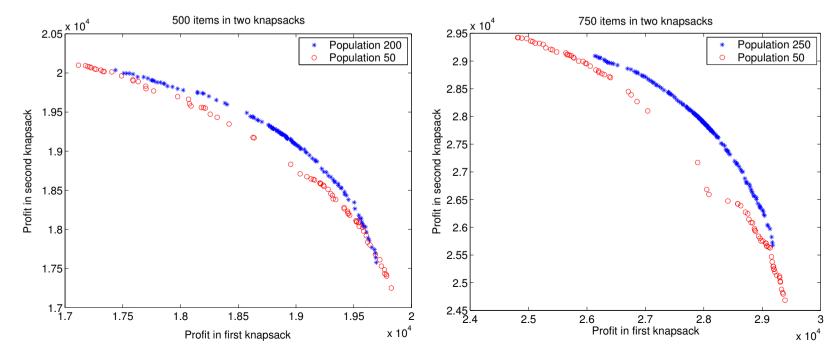
 $x_i - \epsilon \le x'_i \le x_i + \epsilon,$

where ϵ is an error term (0.00001 × x_i)

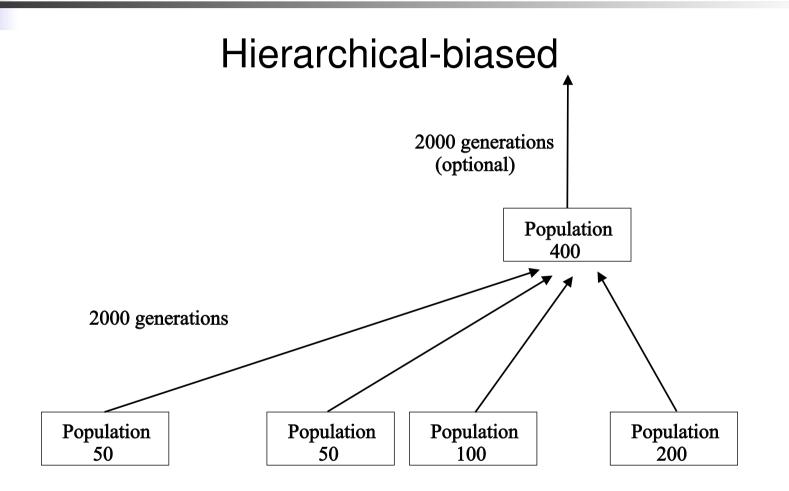
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- Large populations gave higher quality results in the center of the range

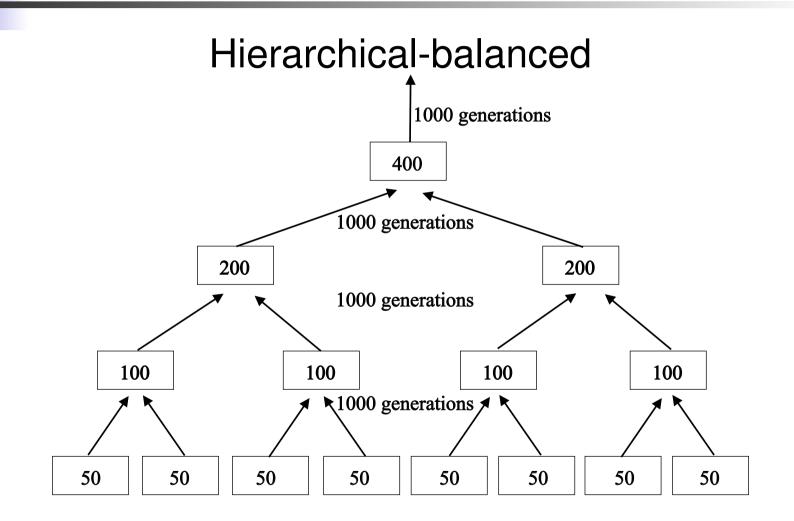
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The Hierarchical Algorithms



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Hierarchical Biased Algorithms

Procedure *Hierarchical-biased* (*population*) **Begin**

if (populationsize > threshold)
 split population into leftpop and rightpop
 Hierarchical-biased (leftpop)
 Run evolutionary algorithm on rightpop

else

Run evolutionary algorithm on (unsplit) *population* **End**

The Hierarchical Balanced Algorithm

Procedure *Hierarchical-balanced* (*population*) **Begin**

if (populationsize > threshold)
 split population into leftpop and rightpop
 Hierarchical-balanced (leftpop)
 Hierarchical-balanced (rightpop)
 Recombine leftpop and rightpop into population
 Run evolutionary algorithm on population
else

Run evolutionary algorithm on (unsplit) *population*

End

Hierarchical-Biased Algorithms

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hierarchical-biased-2layer algorithm (HBI2)

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hierarchical-biased-2layer algorithm (HBI2)
 hierarchical-biased-flat algorithm (HBIF)





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- Experiments are then extended to some continuous functions
- 30 replicate runs carried out for each set of experiments, and all algorithms use the same total population size and number of generations

Comparisons with other EAs?

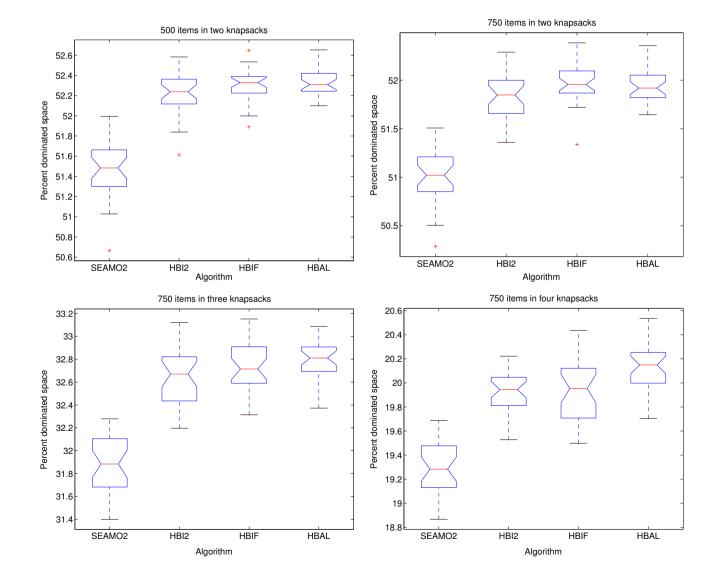
Comparisons with other EAs?

The hierarchical algorithms are compared only with SEAMO2, and not with any other MOEAs

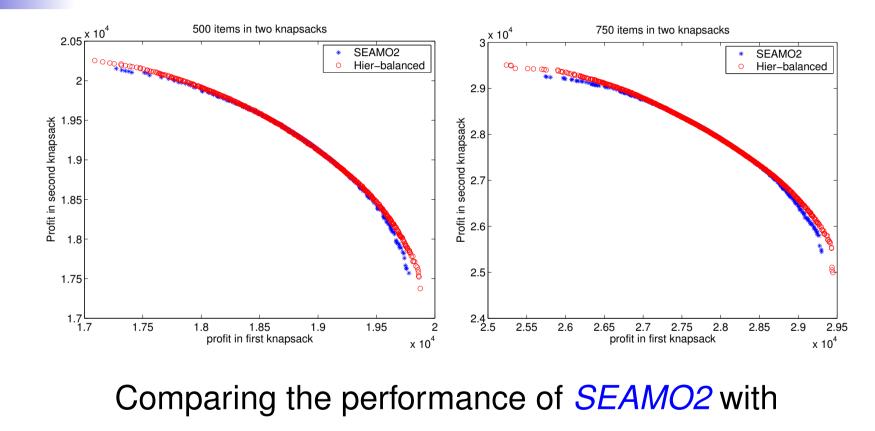
Comparisons with other EAs?

- The hierarchical algorithms are compared only with SEAMO2, and not with any other MOEAs
- SEAMO2 has demonstrated its strength in relation to other EAs elsewhere in a forthcoming GECCO 2004 paper

Results for the MKP, Dominate space, S



Results for Multiple Knapsack Problems

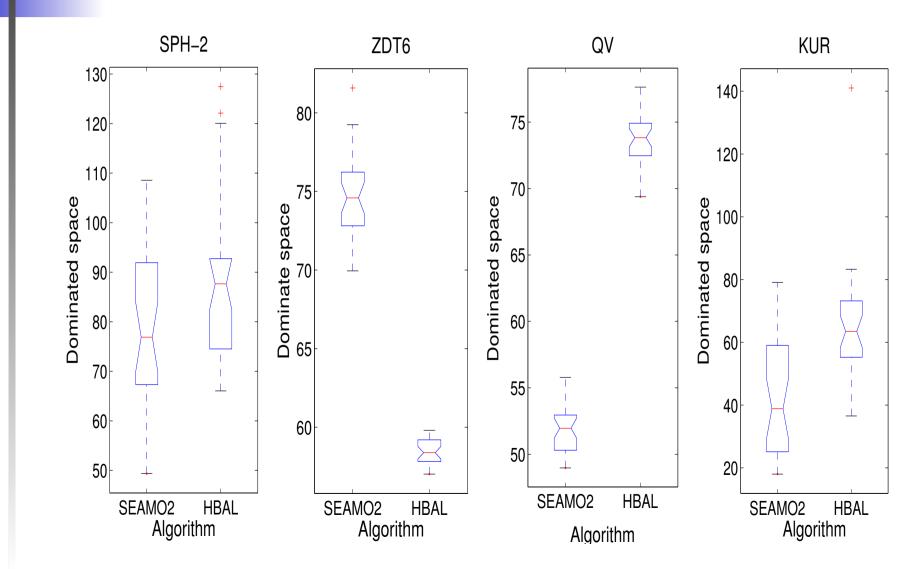


Hierarchical-balanced

Average Coverage, $(A \succeq B)$, on the MKP

Algorithm		Test problems					
A	В	kn500.2	kn750.2	kn750.3	kn750.4		
SEAMO2	HBI2	37.6	50.1	46.4	46.9		
	HBIF	64.9	70.8	61.4	60.1		
	HBAL	22.2	32.8	19.1	21.9		
HBI2	SEAMO2	25.4	15.0	5.2	4.4		
	HBIF	75.4	68.1	50.1	37.2		
	HBAL	20.0	14.8	4.0	6.8		
HBIF	SEAMO2	5.8	2.8	0.8	1.1		
	HBI2	7,7	14.9	7.3	4.9		
	HBAL	5.4	6.1	1.5	2.3		
HBAL	SEAMO2	28.9	21.8	12.8	6.4		
	HBI2	54.7	72.0	44.4	25.2		
	HBIF	72.4	77.1	60.6	50.8		

Continuous Function Results, S



Continuous Functions (cont)

$Coverage\;(A \succeq B)$								
Algorithm		Test problems						
А	В	SPH-2	ZDT6	QV	KUR			
SEAMO2	HBAL	4.4	98.9	20.8	10.1			
HBAL	SEAMO2	5.4	0	21.6	66.2			



Conclusions

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- Better solutions are achieved using large populations and long running times
- Given large computational resources, how do we make best use of them?
- Do we use large single populations or utilize subpopulations?

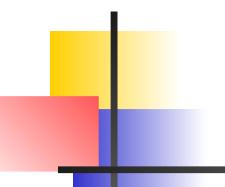


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- Incorporating runs on small and large populations
- Improving the range of solutions, while maintaining their quality
- The hierarchical balanced algorithm performed best







Focus subpopulations on different regions of the Pareto space



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- Try ternary, quadtree etc structures for the hierarchical balanced algorithm



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- Try ternary, quadtree etc structures for the hierarchical balanced algorithm
- Implement a massively parallel version of SEAMO