

## Applications of order based GAs (1)

- Sorting (easy)
- N-queens (not very difficult)
- Routing (tough)
- Scheduling (tough)
- Graph colouring (tough)
- etc.

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## Applications of order based GAs (2)

Precedence constrained job shop scheduling problem

- $J$  is a set of jobs.
- $O_j (j \in J)$  is a set of operations ( $O = \cup O_j$ )
- $M$  is a set of machines
- $Able \subseteq O \times M$  defines which machines can perform which operations, and
- $Pre \subseteq O \times O$  defines which operation should precede which
- $Dur: \subseteq O \times M \rightarrow \mathbb{R}$  defines the duration of  $o \in O$  on  $m \in M$

**The goal is now to find a schedule such that:**

- All jobs are scheduled
- All conditions defined by *Able* and *Pre* are satisfied
- The total duration of the schedule is minimal

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## Applications of order based GAs (2)

Precedence constrained job shop scheduling GA

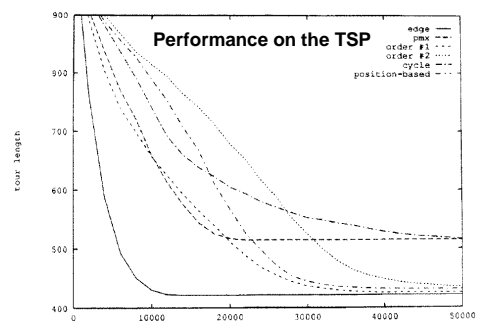
- individuals are permutations of operations
- permutations are decoded to schedules by a decoding procedure
  - take the first (next) operation from the individual
  - look up its machine
  - assign the earliest possible starting time on this machine, subject to
    - machine occupation
    - precedence relations holding for this operation in the schedule created so far
- fitness of a permutation is the duration of the corresponding schedule (to be minimized)
- use any ob-mutation and any ob-crossover
- use roulette wheel selection on inverse fitness
- use random initialization

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## Performance of order based crossovers (1)

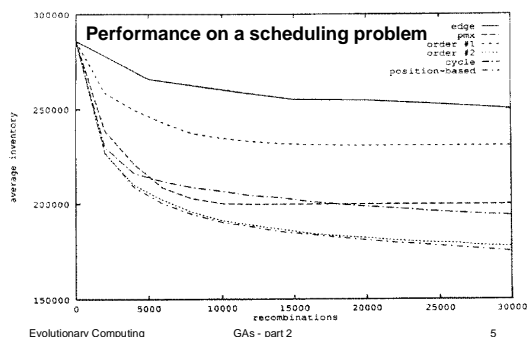


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## Performance of order based crossovers (2)



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## Performance of order based crossovers (3)

**Conclusions:**

- Different operators can perform differently on the same problem.
- The same operator can perform differently on different problems.

**Corollary (bad news):**

There is no generally good advice on the best operator.

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## Selection (1)

**Fitness proportional selection (FPS):**

Expected number of times  $f_i$  is selected for mating is:  $\frac{f_i}{\bar{f}}$

**Disadvantages:**

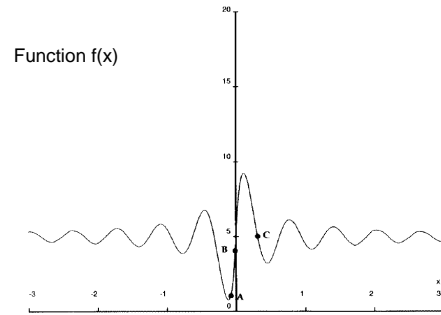
- 1 Outstanding individuals take over the entire population very quickly  $\Rightarrow$  danger for premature convergence.
- 2 Low selection pressure when fitness values are near each other.
- 3 Behaves differently on transposed versions of the same function.

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## Selection (2)

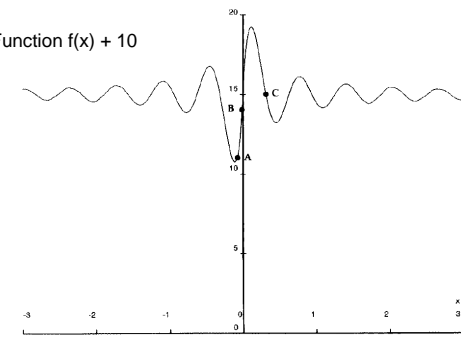
Function  $f(x)$ 

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## Selection (3)

Function  $f(x) + 10$ 

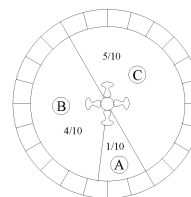
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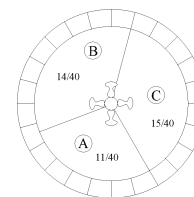
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## Selection (4)

Selection probabilities of the same population on

Function  $f(x)$ 

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Function  $f(x) + 10$ 

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## Selection (5)

A cure for FPS: fitness scaling

**Procedure:**

- 1 Start with the raw fitness function  $f$ .
- 2 Standardise to ensure:
  - Lower fitness is better fitness.
  - Optimal fitness equals 0.
- 3 Adjust to ensure:
  - Fitness values range from 0 to 1.
- 4 Normalise to ensure:
  - The sum of the fitness values equals 1.

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## Selection (6)

A cure for FPS: fitness scaling (continued)

**Details of procedure:**

- Let  $P_t$  be the population at time  $t$ .
- Standardisation yields

$$f_i^s(x) = \begin{cases} f(x) - \min_i(f) & \text{if } f \text{ is to be minimized} \\ \max_i(f) - f(x) & \text{if } f \text{ is to be maximized} \end{cases}$$

- Adjusting yields  $f_i^a$

$$f_i^a(x) = \frac{f_i^s(x)}{\max_i(f_i^s) - \min_i(f_i^s)} = \frac{f_i^s(x)}{\max_i(f_i^s)} \quad \text{By standardisation}$$

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## Selection (7)

- Normalisation yields :

$$f_t^n(x) = \frac{f_t^a(x)}{\sum_{x \in P_t} f_t^a(x)}$$

Note:  $\max_t$  and  $\min_t$  are taken over  $P_t$

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## Selection (8)

## Ranking selection

- Rank individuals according to their fitness
- Use the ranks, rather than the fitness values, to determine the probability of selection
- Mapping from ranks to selection probabilities is arbitrary, for instance linear

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## Selection (8)

## Ranking selection example

3 individuals A, B, C and linear mapping for maximization problem:

- Fitness:  $f(A) = 1$ ,  $f(B) = 4$ ,  $f(C) = 5$ .
- Ranking:  $r(A) = 1$ ,  $r(B) = 2$ ,  $r(C) = 3$ .
- Linear function:

$$h(x) = \min + (\max - \min) \times \frac{(r(x) - 1)}{n - 1}$$

$h(A) = 1$ ,  $h(B) = 3$ ,  $h(C) = 5$

- selection probabilities proportional to  $h$  values:  $h(x)/9$   
 $p_{\text{rank}}(A) \approx 11\%$ ,  $p_{\text{rank}}(B) \approx 33\%$ ,  $p_{\text{rank}}(C) \approx 56\%$ .
- selection probabilities with roulette wheel proportional to  $f$  values:  $f(x)/10$   
 $p_{\text{rw}}(A) = 10\%$ ,  $p_{\text{rw}}(B) = 40\%$ ,  $p_{\text{rw}}(C) = 50\%$ .

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## Selection (9)

## Tournament selection:

- Pick  $k$  individuals randomly, without replacement
- Select the best of these  $k$  comparing their fitness values

$k$  is called the size of the tournament

selection is repeated as many times as necessary

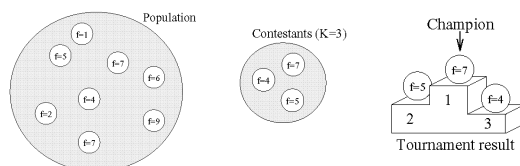
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## Selection (9)

## Tournament selection example



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