Implementation exercises for the course Heuristic Optimization

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¹ Slides based on last year's excersises by Dr. Manuel López-Ibáñez.

Exercise 1.1: Iterative Improvement for the PFSP

Implement perturbative local search algorithms for the PFSP

- Permutation Flow Shop Scheduling Problem (PFSP)
- First-improvement and Best-Improvement
- Transpose, exchange and insert neighborhoods
- Random initialization vs. SLACK heuristic
- Statistical Empirical Analysis

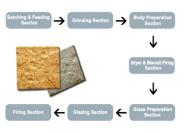
Glazed Tile Production Flow Chart





- Tiles need several processing steps with different machines
- Tiles of different type require specific processing times for each machine
- Goal: find a schedule of the jobs that minimizes an objective function (makespan or total completion time)

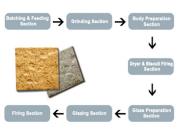
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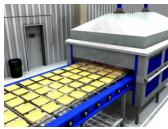




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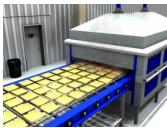




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Flow Shop Scheduling

- Several scheduling problems have been proposed with different formulations and constraints.
- In permutation flow shop problems:
 - jobs composed by operations to be executed on several machines
 - all jobs pass through the machines in the same order
 - all jobs available at time zero
 - pre-emption not allowed
 - each operation has to be performed on a specific machine
 - each job at most on one machine at a time
 - each machine at most one job at a time

- Jobs pass trough all machines in the same order (FCFS queues)
- No constraints: infinite buffers between machines, no blocking, no no-wait requirements (steel production)

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Given

A set of n jobs J_1, \ldots, J_n jobs, where each job J_i consists of m operations o_{i1}, \ldots, o_{im} performed on M_1, \ldots, M_m machines in that order, with processing time p_{ij} for operation o_{ij} .

Due dates

Each job J_i has a *due date* d_i and a priority w_i . Let C_{ij} be the completion time of job J_i on machine M_j , and C_i the completion time of job J_i on the last machine. The tardiness of such a job J_i is $T_i = \max\{C_i - d_i, 0\}$.

Objective

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Computing completion times

$$\begin{array}{ll} C_{\pi(1)j} = \sum_{h=1}^{j} p_{\pi(1)h} & j = 1, \dots m \\ C_{\pi(k)1} = \sum_{h=1}^{k} p_{\pi(h)1} & k = 1, \dots n \\ C_{\pi(k)j} = \max\{C_{\pi(k-1)j}, C_{\pi(k)(j-1)}\} + p_{\pi(k)j} & k = 2, \dots n \\ j = 2, \dots m \end{array}$$

	J_1	J_2	J_3	J_4	J_5
Pi1			4	2	
Pi2	2	1	3		1
p_{i3}	4	2	1	2	

Makespan = 21

Sum of Completion times = 73

Total Weighted Tardiness = 3

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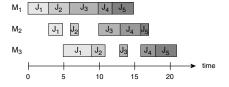
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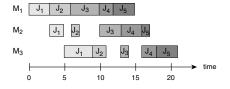
Makespan = 21 Sum of Completion times = 73

Total Weighted Tardiness = 34

Computing completion times

$$\begin{array}{ll} C_{\pi(1)j} = \sum_{h=1}^{j} p_{\pi(1)h} & j = 1, \dots m \\ C_{\pi(k)1} = \sum_{h=1}^{k} p_{\pi(h)1} & k = 1, \dots n \\ C_{\pi(k)j} = \max\{C_{\pi(k-1)j}, C_{\pi(k)(j-1)}\} + p_{\pi(k)j} & k = 2, \dots n \\ j = 2, \dots m \end{array}$$

Job	J_1	J_2	J ₃	J_4	J ₅
p _{i1}	3	3	4	2	3
p_{i2}	2	1	3	3	1
p_{i3}	4	2	1	2	3
di	11	9	10	11	30
W_i	1	2	4	2	3



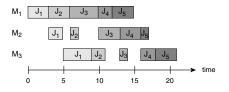
	3	6	10	12	15
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T_i	0	2	4	7	0

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Sum of Completion times = 73

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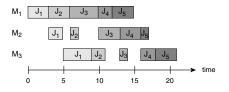
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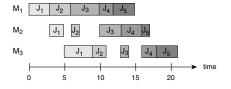
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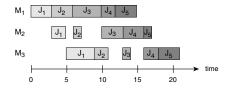
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Implement 12 iterative improvements algorithms for the PFSP

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- Pivoting rule:
 - first-improvement
 - 2 best-improvement
- Neighborhood:
 - Transpose
 - Exchange
 - Insert
- Initial solution:
 - Random permutation
 - SLACK heuristic

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- Pivoting rule:
 - first-improvement
 - Ø best-improvement
- Neighborhood:
 - Transpose
 - Exchange
 - Insert
- Initial solution:
 - Random permutation
 - SLACK heuristic
- 2 pivoting rules \times 3 neighborhoods \times 2 initialization methods = 12 combinations

Implement 12 iterative improvements algorithms for the PFSP

Don't implement 12 programs!

Reuse code and use command-line parameters

```
pfsp-ii --first --transpose --neh
pfsp-ii --best --exchange --random-init
...
```

Iterative Improvement

```
\pi := \text{GenerateInitialSolution} \ ()
while \pi is not a local optimum do
choose a neighbour \pi' \in \mathcal{N}(\pi) such that F(\pi') < F(\pi)
\pi := \pi'
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\begin{split} \pi &:= \texttt{GenerateInitialSolution}\,(\,) \\ \textbf{while} \, \pi \text{ is not a local optimum } \textbf{do} \\ &\quad \text{choose a neighbour } \pi' \in \mathcal{N}(\pi) \text{ such that } F(\pi') < F(\pi) \\ &\quad \pi := \pi' \end{split}
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Which neighbour to choose? Pivoting rule

- Best Improvement: choose best from all neighbours of s
 - ✓ Better quality
 - X Requires evaluation of all neighbours in each step
- First improvement: evaluate neighbours in fixed order and choose first improving neighbour.
 - More efficient
 - X Order of evaluation may impact quality / performance

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```

Initial solution

- Random permutation
- SLACK heuristic

Iterative Improvement

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```

SLACK heuristic

Construct the solution inserting **one job at a time**, by always selecting the one that minimizes the weighted earlyness.

The weighted earlyness of job J_i is computed as $w_i \cdot (d_i - C_i)$.

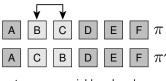
Note: the solution is constructed incrementally, and at each iteration C_i corresponds to the makespan of the partial solution.

Iterative Improvement

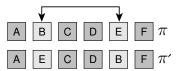
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Which neighborhood $\mathcal{N}(\pi)$?

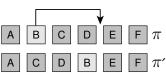
- Transpose
- Exchange
- Insertion



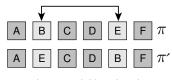
transpose neighbourhood



exchange neighbourhood



insert neighbourhood



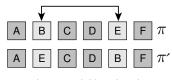
exchange neighbourhood

Example: Exchange π_i and π_j (i < j), $\pi' = \text{Exchange}(\pi, i, j)$

Only jobs after i are affected!

Do not recompute the evaluation function from scratch!

Equivalent speed-ups with Transpose and Insertion



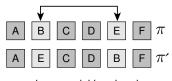
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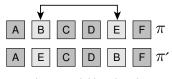
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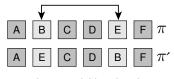
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Instances

- PFSP instances with 50, 60, 70, 80, 90, and 100 jobs, and 20 machines.
- More info: http://iridia.ulb.ac.be/~stuetzle/Teaching/HO/

Experiments

Apply each algorithm k once to each instance i and compute:

- 1 Relative percentage deviation $\Delta_{ki} = 100 \cdot \frac{\cos t_{ki} \text{best-known}_i}{\text{best-known}_i}$
- 2 Computation time (t_{ki})

Report for each algorithm k

- Average relative percentage deviation
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Is there a statistically significant difference between the solution quality generated by the different algorithms?

Statistical test

- Paired t-test
- Wilcoxon signed-rank test

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- Statistical hypothesis tests are used to assess the validity of statements about properties of or relations between sets of statistical data.
- The statement to be tested (or its negation) is called the *null hypothesis* (H₀) of the test.
 Example: For the Wilcoxon signed-rank test, the null hypothesis is that 'the median of the differences is zero'.
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Exercise 1.2 VND algorithms for the PFSP

Implement 4 VND algorithms for the PFSP

- Pivoting rule: first-improvement
- Neighborhood order:
 - $lacktrianspose
 ightarrow \operatorname{exchange}
 ightarrow \operatorname{insert}$
 - 2 transpose \rightarrow insert \rightarrow exchange
- Initial solution:
 - Random permutation
 - SLACK heuristic

Exercise 1.2 VND algorithms for the PFSP

Variable Neighbourhood Descent (VND)

```
k neighborhoods \mathcal{N}_1, \ldots, \mathcal{N}_k
\pi := GenerateInitialSolution()
i := 1
repeat
   choose the first improving neighbor \pi' \in \mathcal{N}_i(\pi)
   if \nexists \pi' then
      i := i + 1
   else
      \pi := \pi'
      i := 1
until i > k
```

Exercise 1.2 VND algorithms for the PFSP

Implement 4 VND algorithms for the PFSP

- Instances: Same as 1.1
- Experiments: one run of each algorithm per instance
- Report: Same as 1.1
- Statistical tests: Same as 1.1