IEEE CEC 2018

A Decomposition-based Local Search Algorithm for Multi-objective Sequence Dependent Setup Times Permutation Flowshop Scheduling

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July 11, 2018

Schedule

Flowshop Scheduling Problem (FSP)

- FSP serves as a model for several real-world problems from manufacturing, engineering, and other fields of application
- Different objectives have been considered as optimization goals, e.g., i) *Makespan, ii) Total Flowtime, and iii) Total Tardiness*

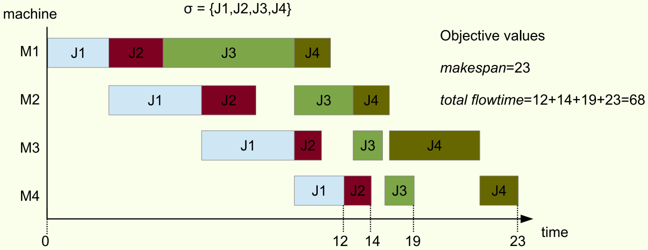


Figure: An example of flow-shop scheduling problem with 4 jobs and 4 machines

- Problem restriction: When the sequence of jobs is the same for all machines, the problem is denoted Permutation Flowshop Scheduling (PFSP)
- Goal: To find a permutation of jobs such that a criteria is minimized

Flowshop Scheduling Problem (FSP)

- **Setup Times**: In FSP, setups can reflect some non-productive operations that have to be processed on machines that are not part of the processing times of the jobs
- **Sequence-dependent:** When the setups dependents on the job being processed and on the next job in the sequence
- **Multi-objective optimization:** Multiple PFSP objectives to be optimized simultaneously.

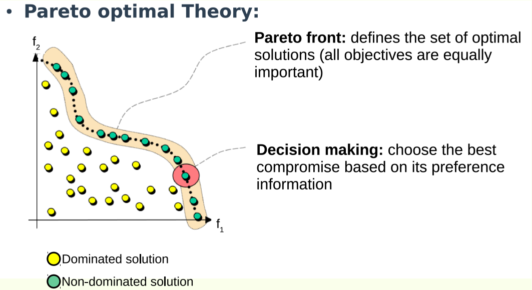


Figure: An example of maximization of two objectives

PFSP solvers

- Heuristics Algorithms
- Meta-heuristics Algorithms
  - Evolutionary Strategies (e.g., genetic search)
  - Simulated Annealing
  - Iterated Local Search (ILS)
- Hybrid Approaches
  - Example: Heuristic + Evolutionary Strategies + local search
  - Goal: An effective balance between *Convergence* $\times$ *Diversity*

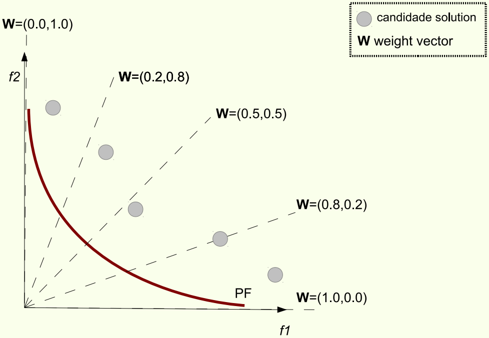
Concept Definition: Iterated Local Search

- A solution $\mathbf{x}'$ is a neighbor solution of $\mathbf{x}$ if $\mathbf{x}'$ can be achieved by a single move from $\mathbf{x}$, and its depends on a basic underlying *operator* and a given *distance* between any two solutions

- **Iterated Local Search (ILS):** consists of repeatedly applying local search procedures. When the search is trapped in a local optimal solution, ILS can perturb the solution to allow the search to escape from the trap without losing many of the good properties of the current solution

Concept Definition: Multi-objective EA based on Decomposition

- **MOEA/D framework**: The idea is to decompose a multi-objective problem into a number of scalar single-objective subproblems (by using a set of weight vectors and an aggregation function). Each subproblem is optimized using an EA and the information mainly from its several neighboring subproblems
- Well effective for solving combinatorial optimization problems with 2 and 3 objectives.



Multi-objective ILS based on Decomposition

- Ingredients:
  - Decomposition strategy: *Weighted Sum Approach*
  - Heuristic initialization of the population using variants of the *NEH heuristic*
  - Local search operators in a space of permutations: *1-insert* and *1-interchange* (*exploitation*)
  - Shaking procedure: to move the current solution of a subproblem to another region of the search (*exploration*)

Multi-objective ILS based on Decomposition

- **Input:**
  - N: population size
  - $\boldsymbol{W}^1, ..., \boldsymbol{W}^N$: distributed weight vectors
  - T: neighborhood size for update
  - n_r: maximum replacements allowed by a new solution
  - n_{sh}: number of random *insert moves*
- **Output:**
  - *Pop*: The final set of N solutions
  - *External Pareto* (all non-dominated solutions found)
- **Initialization**: $Pop := \{\sigma^1, ..., \sigma^N\}$
- *While a stopping criterion is not met:*
  - **Search Process:** For each $k \in 1, ..., N$:
    - **Generate** σ' using a LS move on σ^k and compute $F(\sigma')$
    - **Update** *Pop* with σ' according to the scalar aggregation function and the T closest neighbor subproblems
    - **Check** if the subproblem has not been improved after n generations
    - **Update** *External Pareto*

Experimental setup

- **Benchmark:** 220 instances extended from the Taillard benchmark that vary according to the number of jobs $n = \{20, 50, 100\}$, number of machines $m = \{10, 20\}$, and setup times.
- **Bi-objective case:** *makespan* and *total weighted tardiness*
- **Comparison:**
  - The best-known results from the literature (in the form of approximated *Pareto fronts*) obtained by the best performer algorithms (RIPG and MOSA_VM)
  - MOEA/D (which employs genetic operators, specially toileted for permutation problems)
- **Performance assessment:** 1) Hypervolume, 2) Coverage, and 3) *Empirical Attained function* (EAF)

Experimental setup

- Parameters settings: $N = 100$, $T = 20$, $n_r = 2$, $n_{sh} = 14$ random *insert moves*
- Maximum Generations: $1000n$
- 20 independent runs for each algorithm and problem instance
- Statistical tests: *Friedman's* ranked based at 95% of confidence level and *post-hoc* Nemenyi

Results: MOLS/D components

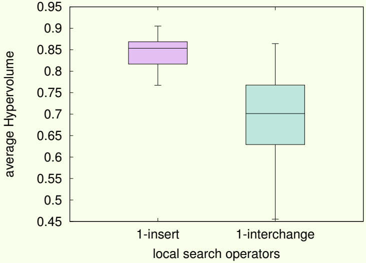


Figure: Boxplot of the average *HV* values obtained by MOLS/D using the *1-insert move* and the *1-interchange move*.

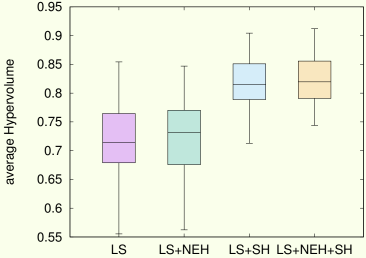
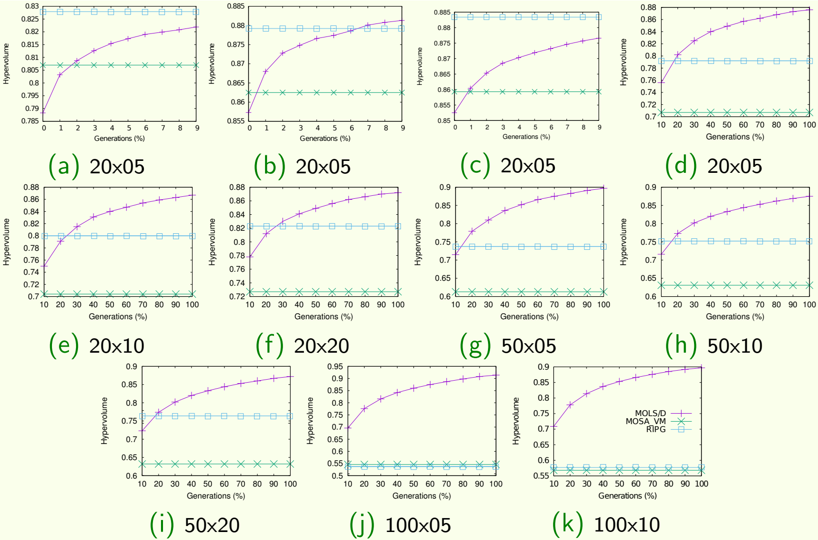


Figure: Boxplot of the average *HV* values obtained by four algorithm configurations: (i) without both heuristic initialization and shaking procedure (LS), (ii) only with the heuristic initialization (LS+NEH), (iii) only with the shaking procedure (LS+SH), and (iv) with all the components together (LS+NEH+SH).

Results: Comparison to the best-known results from literature



(a) 20x05 (b) 20x05 (c) 20x05 (d) 20x05

(e) 20x10 (f) 20x20 (g) 50x05 (h) 50x10

(i) 50x20 (j) 100x05 (k) 100x10

Figure: Average *HV* values obtained by MOLS/D throughout 10 different stages of the search compared to the *HV* obtained by the reference sets of MOSA and RIPG (constant lines) for the different problem scales (11 in total)

Results: Comparison results

Table: Average *HV* values obtained by MOLS/D, MOEA/D, MOSA_VM, and RIPG

problem $n \times m$	SSD50				SSD125			
	MOLS/D	MOEA/D	MOSA_VM	RIPG	MOLS/D	MOEA/D	MOSA_VM	RIPG
20×05	**0.847**	0.649	0.832	**0.852**	**0.822**	0.542	0.799	**0.835**
20×10	**0.893**	0.774	0.874	**0.890**	**0.867**	0.684	0.852	**0.871**
20×20	**0.874**	0.712	0.856	**0.881**	**0.863**	0.668	0.834	**0.870**
50×05	**0.877**	0.413	0.704	0.788	**0.869**	0.357	0.656	0.812
50×10	**0.869**	0.440	0.706	0.801	**0.856**	0.412	0.659	0.816
50×20	**0.867**	0.487	0.717	0.817	**0.872**	0.445	0.678	0.831
100×05	**0.897**	0.348	0.612	0.735	**0.874**	0.251	0.509	0.764
100×10	**0.875**	0.382	0.632	0.752	**0.862**	0.309	0.517	0.767
100×20	**0.873**	0.377	0.633	0.763	**0.885**	0.347	0.554	0.787
200×10	**0.914**	0.320	0.549	0.538	**0.906**	0.285	0.420	0.549
200×20	**0.896**	0.375	0.565	0.574	**0.906**	0.369	0.479	0.627

Results: Diff-EAF tool

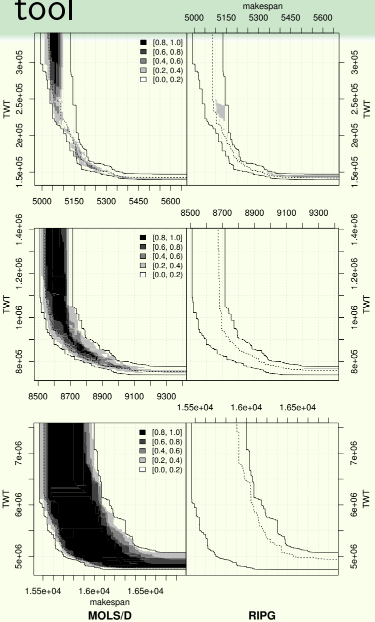


Figure: Diff-EAF between MOLS/D (left) and RIPG (right) for SSD50_051 (50 $\times$ 20) (top), SSD50_071 (100 $\times$ 20) (middle), and SSD50_101 (200 $\times$ 20) (bottom).

Final Considerations

- A simple yet efficient population-based algorithm: Multi-objective Iterated Local Search Algorithm based on Decomposition
- Hybrid approach: heuristic + ILS strategy + diversity mechanism
- Experimental study using 220 benchmark instances with different problem scales
- Contributions:
  - MOLS/D outperforms a tailored MOEA/D
  - MOLS/D is able to achieve better results than the state-of-the-art approaches for the benchmark considered
  - We made our results (in the form of approximated *Pareto fronts*) available for further investigations by other researches. Available at https://github.com/murilozangari/sdst results.
- Future work:
  - The application of MOLS/D to solve i) SDST flowshop with three objectives, ii) flexible job-shop scheduling, and iii) other kind of permutation problems.

Acknowledgment

This work has been supported by:

- PNPD/CAPES (Brazilian Program of Post-Doctoral)
- CNPq (Productivity Grant Nos. 306754/2015-0)
- Research Groups 2013-2018 (IT-609-13) programs (Basque Government)
- TIN2016-78365-R (Spanish Ministry of Economy, Industry, and Competitiveness)

Thank you!

UEM Universidade Estadual de Maringá

GPEA Grupo de Pesquisa em Engenharia de Algoritmo

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