Automatic Design of Multi-Objective Local Search Algorithms
Case Study on a bi-objective Permutation Flowshop Scheduling Problem

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Context
Metaheuristics: Highly Tunable Algorithms

Key Points

▶ Approximation algorithms for optimisation problems
▶ Few assumptions about the problem
▶ Many parameters and strategies

Performance

▶ Differs with the problem
▶ Differs with the instance
▶ Depends on its configuration (set of parameter values)
Context
Automatic Algorithm Configuration

Single-Objective Configuration

- Learn the optimal configuration on a training instance set
- irace [López-Ibáñez et al., 2016], ParamILS [Hutter et al., 2009], SMAC [Hutter et al., 2010], GGA++ [Ansótegui et al., 2015], . . .

Multi-Objective Configuration

- MO-ParamILS [Blot et al., LION 2016]
- Optimise multiple performance indicators
Context

Configuring Multi-Objective Algorithms

Performance Indicators

- Convergence
- Diversity
- Spread
- Size

Multi-Objective Configuration

- Configuring a MO algorithm is a MO problem [Blot et al., EMO 2017]
Motivation
Designing Efficient Multi-Objective Metaheuristics

Question
▶ How efficient is MO-AAC to design MO metaheuristics?

Case Study
▶ MO-ParamILS
▶ Multi-objective Local Search algorithms
▶ Bi-objective Permutation Flowshop Scheduling Problem
Case Study
MOLS: Multi-objective Local Search Algorithms

Key Points

- Efficient metaheuristics
- Used on many problems (e.g., scheduling, routing, assignment)
- Many strategies and parameters

In the Literature

- Methods
  - Pareto Archived Evolution Strategy (PAES, 1999, 2000)
- Unifications
  - Stochastic Pareto Local Search (SPLS, 2012)
  - Dominance-based Multi-objective Local Search (DMLS, 2012)
Multi-Objective Local Search Algorithms

Simple Workflow

Example Parameters

- Selection
  - Type and number of solutions
- Exploration
  - Neighbourhood
  - Reference point
  - Type and number of neighbours
- Archive
  - Archive size
  - Type of solutions
Multi-Objective Local Search Algorithms

Iterated Workflow

Iterated Local Search (ILS)

[Lourenço et al., 2003]
MOLS Adaptability

Highly Configurable

- Initialisation
- Selection
- Exploration
- Archive
- Iteration
- Perturbation
## Possible MOLS Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Type</th>
<th>Parameter values</th>
</tr>
</thead>
<tbody>
<tr>
<td>initStrat</td>
<td>category</td>
<td>{rand, neh, ig}</td>
</tr>
<tr>
<td>selectStrat</td>
<td>category</td>
<td>{all, rand, newest, oldest}</td>
</tr>
<tr>
<td>selectSize</td>
<td>integer</td>
<td>1+</td>
</tr>
<tr>
<td>explorStrat</td>
<td>category</td>
<td>{all, imp, ndom, ...}</td>
</tr>
<tr>
<td>explorRef</td>
<td>category</td>
<td>{pick, arch}</td>
</tr>
<tr>
<td>explorSize</td>
<td>integer</td>
<td>1+</td>
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<tr>
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<td>category</td>
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<td>1+</td>
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<td>1+</td>
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<td>{restart, kick}</td>
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<td>1+</td>
</tr>
<tr>
<td>perturbStrength</td>
<td>integer</td>
<td>1+</td>
</tr>
</tbody>
</table>
Experimental Protocol

Goal: Compare MO-AAC Performance to Exhaustive Analysis

MO-ParamILS

- Training
- Validation
- Test

Exhaustive Analysis

- Every possible configuration
- Only on the test set

MOLS

- Optimise:
  - Convergence
  - Distribution

- Minimise:
  - 1 - Hypervolume
  - $\Delta$ Spread
MO-ParamILS

Training

Problem space

\( f_2 \)
\( f_1 \)

(Execution on single instance)

- For every configuration
  - multiple runs
  - multiple instances
- Average HV and Δ Spread over multiple runs
MO-ParamILS

Training

Problem space

Configuration space

(average over training instances)

Estimation for a single configuration

(execution on single instance)
MO-ParamILS

Training

- iteratively investigates configurations
- refining quality estimations
- returns non-dominated
- shuffles training instances

Configuration space

\[ \Delta \]

\[ 1-HV \]

(average over training instances)
MO-ParamILS

Training

- iteratively investigates configurations
- refining quality estimations
- returns non-dominated
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Configuration space

\[
\Delta \rightarrow 1 - HV
\]

(average over training instances)
MO-ParamILS

Training

- iteratively investigates configurations
- refining quality estimations
- returns non-dominated
- shuffles training instances

Configuration space

△

1−HV

(average over training instances)
MO-ParamILS Protocol

Training, Validation, Test

Training

\[
\Delta \rightarrow 1-HV
\]

(average over training instances)

- Training
  - 30 training runs
  - different instance subsets
  - incomparable quality estimation

- Validation
  - all training configurations
  - all training instances
MO-ParamILS Protocol
Training, Validation, Test

Validation

\[ \Delta \]
\[ 1 - HV \] (average over training instances)

- **Training**
  - 30 training runs
  - different instance subsets
  - incomparable quality estimation

- **Validation**
  - all training configurations
  - all training instances
MO-ParamILS Protocol

Training, Validation, Test

Validation

\[ \Delta \]

(average over training instances)

Test

\[ \Delta \]

(average over test instances)
Experimental Protocol

Summary

Permutation Flowshop Scheduling Problem

- Classical Taillard instances
- Bi-objective optimisation:
  - Makespan
  - Flowtime

3 scenarios:
- 20-job instances
- 50-job instances
- 100-job instances

189 MOLS Configurations

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<td>{all, rand, new, old}</td>
</tr>
<tr>
<td>selectSize</td>
<td>{1, 3}</td>
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<tr>
<td>explorStrat</td>
<td>{all, imp, ndom}</td>
</tr>
<tr>
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<td>{pick, arch}</td>
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Total time

<table>
<thead>
<tr>
<th>Approach</th>
<th>20-job</th>
<th>50-job</th>
<th>100-job</th>
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</thead>
<tbody>
<tr>
<td>Training</td>
<td>36 min</td>
<td>90 min</td>
<td>3 hours</td>
</tr>
<tr>
<td>MO-AAC</td>
<td>2 days</td>
<td>7 days</td>
<td>15 days</td>
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<tr>
<td>Exhaustive</td>
<td>46 days</td>
<td>115 days</td>
<td>230 days</td>
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</table>
Results

Exhaustive analysis

PFSP Taillard instances – 50 jobs

PFSP Taillard instances – 100 jobs

Exploration / Selection Strategies

▶ ∆ all
▶ o imp
▶ + ndom
▶ □ all
▶ □ newest
▶ □ oldest
▶ □ rand
Results

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Exploration / Selection Strategies

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Results
Multi-Objective Automatic Design

PFSP Taillard instances – 50 jobs

Optimal Configurations

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Multi-Objective Automatic Design

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PFSP Taillard instances – 100 jobs

1 - Hypervolume

Δ Spread

1 - Hypervolume

Blot et al.  Automatic Design of Multi-Objective Local Search Algorithms
Conclusion

Main Contribution

▶ Efficient Automatic design of MOLS algorithms for bi-objective PFSP

Perspectives

▶ Investigate automatic design on other problems
  ▶ e.g., MO-TSP, MO-QAP
▶ Extends to other algorithms
  ▶ e.g., GA, EA

Additional Contribution

▶ New MOLS generalisation
Wrap up

Take-home Message 1

- Configuring a MO algorithm is a MO problem [Blot et al., EMO 2017]

Take-home Message 2

- Use configurable algorithms
  - Or expose tunable parameters
- Propose new components and strategies
- Design the final algorithm automatically