On the Effect of Local Search in the Multi-objective Evolutionary Discovery of Software Architectures

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Introduction

Search Based Software Engineering

Search Based Software Engineering ➤ Search Based Software Design ➤ Architecture Discovery

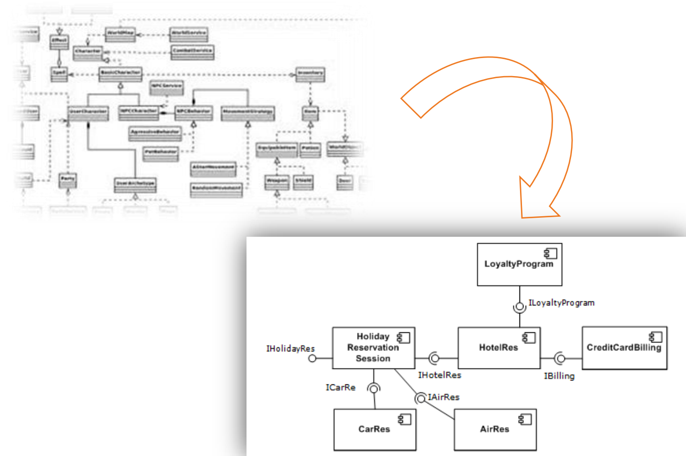
- **Evolutionary methods in software design**
  - ➢ Efficient exploration of design alternatives
  - ➢ Multi-objective search

- **Software architectures**
  - ➢ Important design artefacts in the early software conception
  - ➢ Identification of functional blocks and their interactions

Introduction

Multi-objective evolutionary discovery of architectures

We want to automatically identify the component-based architecture of a system from its analysis model (represented as a class diagram)



NSGA-II

- Component diagrams encoded as trees
- Four objective functions: design metrics
- The mutation performs 5 architectural transformations
- Closer to human-designed architectures

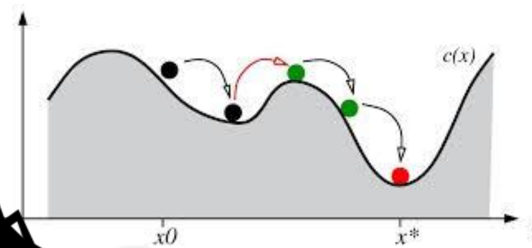
Metric	Formula
ICD: Intra-modular Coupling Density	$ICD_i = ((\#cl_t - \#cl_i)/\#cl_t) \cdot (CI_i^{in}/(CI_i^{in} + CI_i^{out}))$ $ICD = \sum_{i=1}^{n} ICD_i/n$
ERP: External Relations Penalty	$ERP = \sum_{i=1}^{n} \sum_{j=i+1}^{n} (w_{as} \cdot n_{as_{ij}} + w_{ag} \cdot n_{ag_{ij}}$ $+ w_{co} \cdot n_{co_{ij}} + w_{ge} \cdot n_{ge_{ij}})$
CS: Critical size	$CS = \sum_{i=1}^{n} CC_i,\ CC_i = 1\ if\ \#cl_i > threshold,\ 0\ otherwise$
CB: Component Balance	$SB(n) = \frac{n-\gamma}{\mu-\gamma}\ if\ n < \mu\ ,\ = 1 - \frac{n-\mu}{\omega-\mu}\ if\ \mu < n < \omega\ ,\ = 0\ if\ n \geq \omega$ $CSU(n) = 1 - Gini(\{\#cl_i \forall i \in [1, n]\})\ ,\ CB = SB(n) \cdot CSU$

RQ: How can local search be effectively integrated in the multi-objective evolutionary discovery of software architectures?

Introduction
Multi-objective memetic algorithms

Evolutionary algorithm (MOEA) + **Local search (LS)** = **Memetic algorithm (MOMA)**

- **Local search** techniques
  a. Hill climbing (HC)
  b. Simulated annealing (SA)
  c. Tabu search (TS)



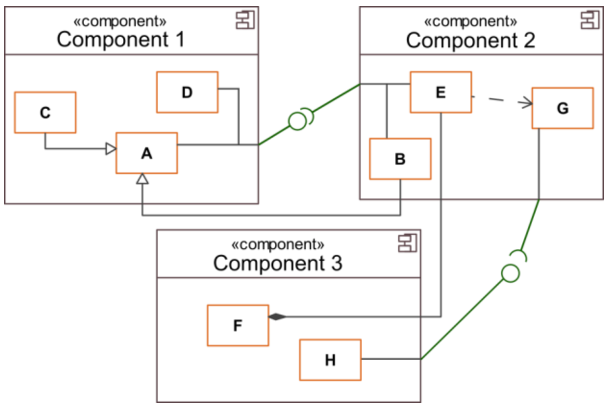
Local search
- Neighbourhood
- Algorithm
- Comparison criterion

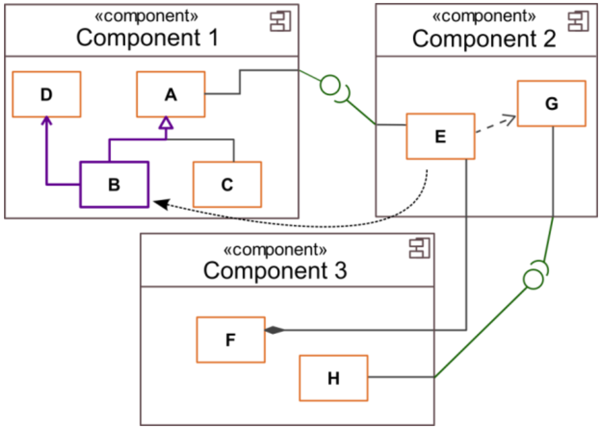
Evolutionary search
- Selection of solutions
- Step of the search
- Number of evaluations

Proposed MOMAs
Local search procedure

- Exploration of the **neighbourhood**:
  - ➢ A random class is reallocated
  - ➢ HC/SA: 1 neighbour/iteration
  - ➢ TS: 5 neighbours/iteration
- **Comparison criterion**:
  - ➢ Dominance (D)
  - ➢ Weights (We)
  - ➢ Best objective (B)
  - ➢ Worst objective (Wo)

Initial solution



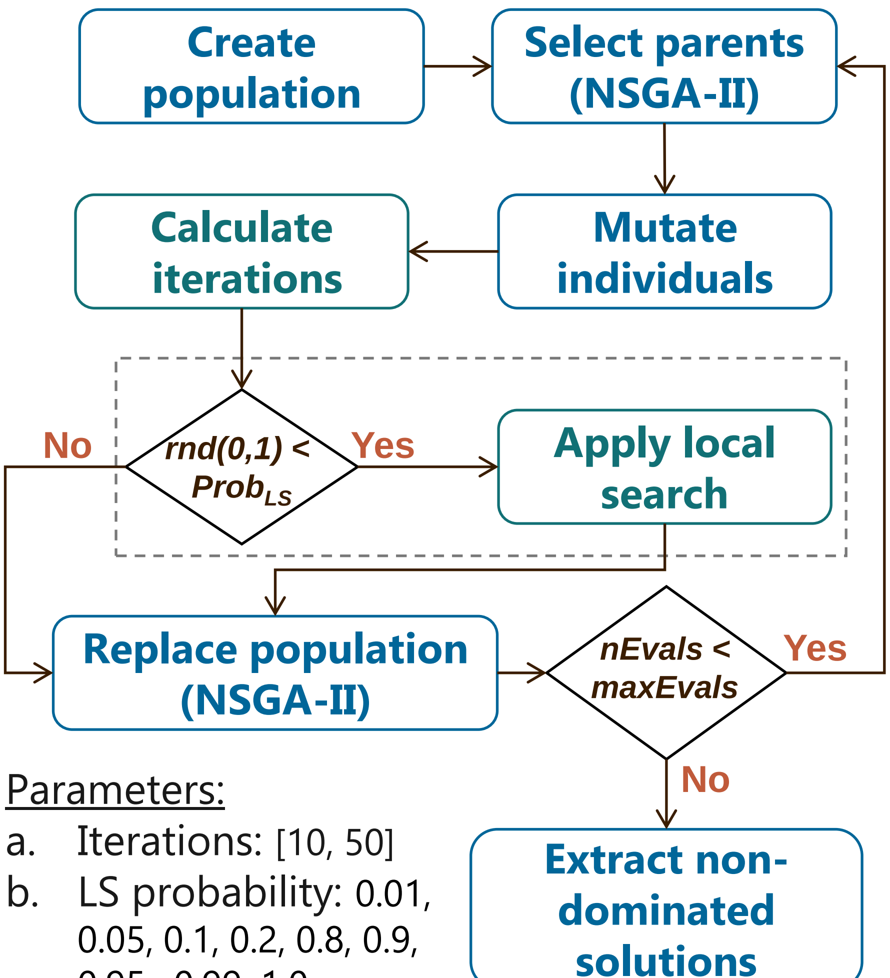


Neighbour solution

Proposed MOMAs

MOEA(LS) and MOEA+LS

MOEA(LS) : LS as a genetic operator

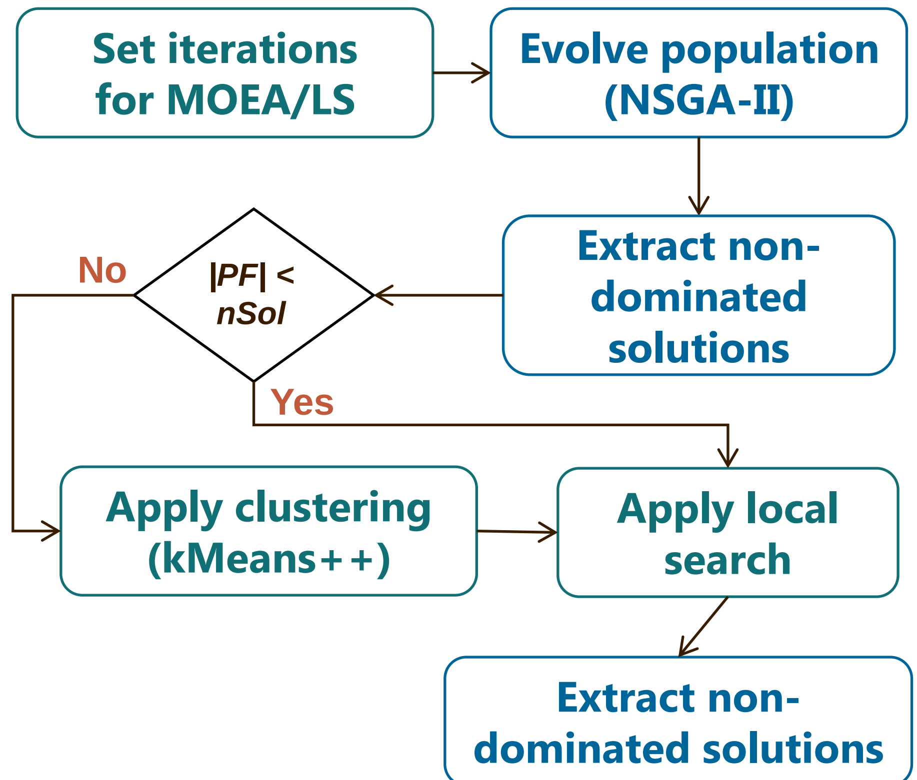


Parameters:

a. Iterations: [10, 50]

b. LS probability: 0.01, 0.05, 0.1, 0.2, 0.8, 0.9, 0.95, 0.99, 1.0

MOEA+LS: LS as post-processing



Parameters:

a. Iterations: 50, 100, 200

b. Solutions (%): 10, 15, 20

Experiments and results
Analysis of quality indicators

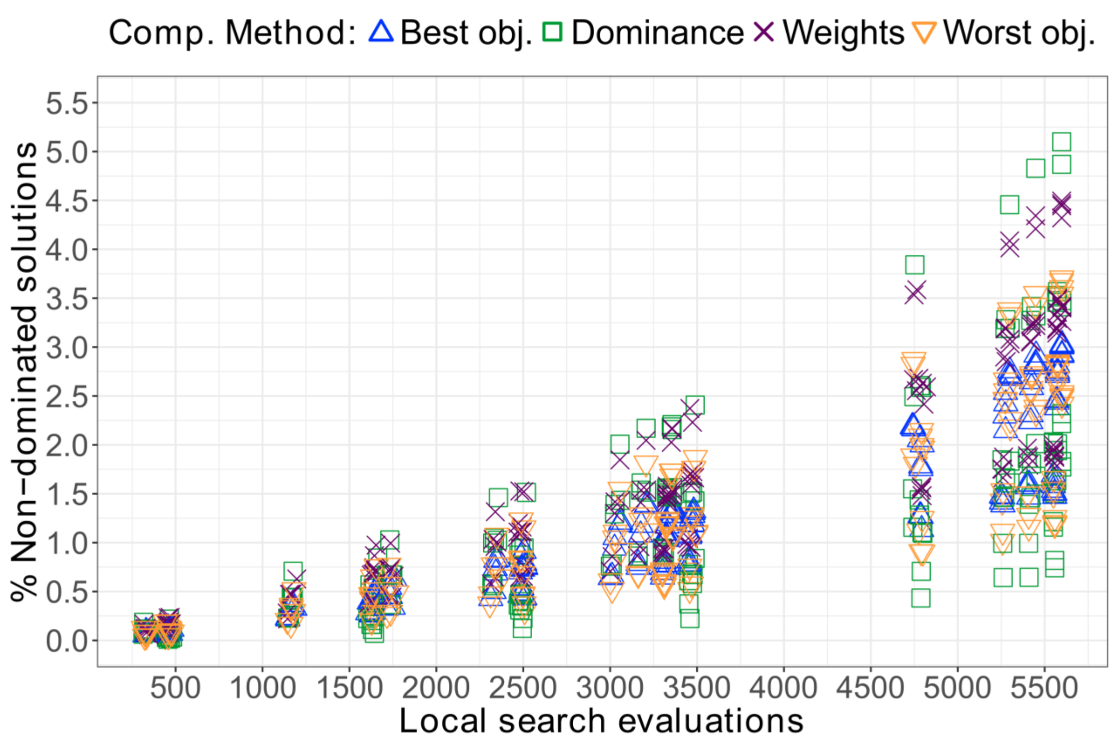
- **Two Set Coverage**
  - TSC = 0 for all comparisons between NSGA-II and MOMA
  - Local search **does not decrease** the efficiency of NSGA-II
- **Spacing**
  - Percentage of **improvement**
    - Few iterations of LS
    - HC/SA vs. TS
    - Different behaviours in MOEA+LS
  - **Effect size** (Cliff's Delta test)
    - Influence of the problem instance
    - MOEA+LS with HC/SA and weights

24 (+1) algorithms:
MOEA(LS) | MOEA+LS
HC | SA | TS
D | We | B | Wo
Common configuration:
150 individuals
24000 evaluations
6 design problems
30 random seeds

		HC	SA	TS
MOEA(LS)	D	[-2.75, 6.66]	[-0.51, 4.02]	[0.07, 4.15]
	We	[0.32, 8.72]	[0.14, 5.74]	[-0.58, 4.80]
	B	[-0.12, 6.49]	[-0.62, 8.53]	[-0.53, 3.55]
	Wo	[-2.76, 6.58]	[-0.56, 5.54]	[-0.13, 3.16]
MOEA+LS	D	[-3.61, 6.68]	[-4.30, 1.95]	[-3.84, -1.79]
	We	[-1.62, 29.47]	[-2.89, 27.42]	[-3.39, 2.11]
	B	[-3.48, 6.32]	[-3.06, 5.50]	[-4.07, -2.04]
	Wo	[-1.77, 14.23]	[-3.92, 11.41]	[-3.55, 0.08]

Experiments and results
Influence on the Pareto Front

- **The number of solutions is similar**
  - Only a small decrease in two problem instances with MOEA+LS
- **Generation of new non-dominated solutions**
  - MOEA(LS):
    - HC > 3%
    - Methods *D* and *We*
  - MOEA+LS:
    - Low percentages
    - Weights are effective



Concluding remarks

- From the **experimental outcomes**:
  - ✓ Local search can enhance the **diversity of solutions**
  - ✓ Influence of the **comparison criterion and algorithm**
  - ✓ Differences among **problem instances**

- **Future work**
  - ➢ **Domain knowledge** to guide the generation of neighbours
  - ➢ Scalability in a **many-objective** space

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Thanks!

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