Evolutionary composition of QoS-aware web services: a many-objective perspective

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Expert System with Applications, vol. 72, pp. 357-370. 2017.

Jornadas de Ingeniería del Software y Bases de Datos. Sevilla, 16-19 de septiembre de 2018

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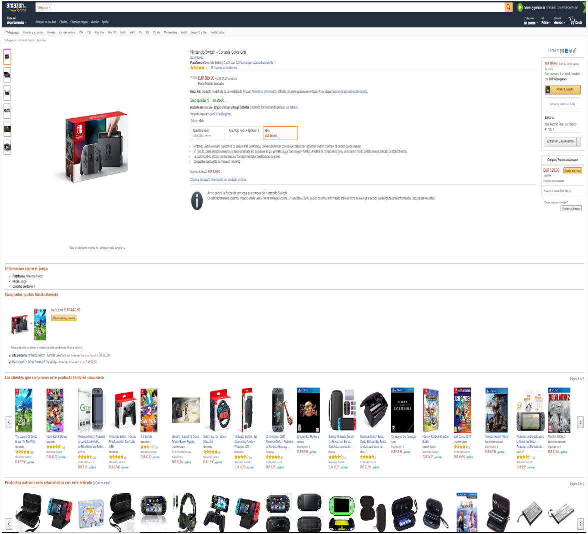
Introduction

Context

What do they have in common?

They develop their core applications as a set of services (orchestrated under a global user interface)

Context



- Order management Service
- Product Search Service
- Product info & details Service
- Order analysis service
- Customer reviews & questions Service
- ...

Context

QoS-aware web service composition (QoSWSC):

- Integration of services (either third-party or in-house): authentication, persistent storage, etc.
- Quality of Service (QoS) can depend on external services.
- The Service Level Agreement (SLA) defines possible alternatives and the configuration of the service providers.

QoSWSC as a search problem:

- Optimal choice of candidate services for a given workflow.
- Some multi-objective approaches, optimising between 3 and 5 objectives: response time vs. reliability, throughput vs. cost.

Our contribution

- Addresses the problem from a many-objective perspective, taking into account additional QoS properties as objectives.
- Studies the influence of the characteristics that define the QoS-aware web service composition problem.
- Compares the performance of different families of multi- and many-objective evolutionary algorithms.

Problem definition

Some definitions

Task (t_i)

Each service that requires a choice among alternative providers or SLAs.

Candidate service ($s_{i,j}$)

Each available implementation of t_i (different provider or SLA).

Composition structure

The set of building blocks that orchestrates the complex service.

Some definitions

Binding (χ)

The selection of one candidate service for each task, i. e. a solution to the problem.

QoS Property (q)

A design or runtime feature that should be satisfied in the global solution.

Utility function (U_q)

A specific expression to aggregate the set of the QoS values of $s_{i,j}$ for each q, also considering the composition blocks.

QoS Properties

The following QoS properties are simultaneously optimised:

1. *Response time* (↓)
2. *Availability* (↑)
3. *Reliability* (↑)
4. *Throughput* (↑)
5. *Latency* (↓)
6. *Successability* (↑)
7. *Compliance* (↑)
8. *Best practices* (↑)
9. *Documentation* (↑)

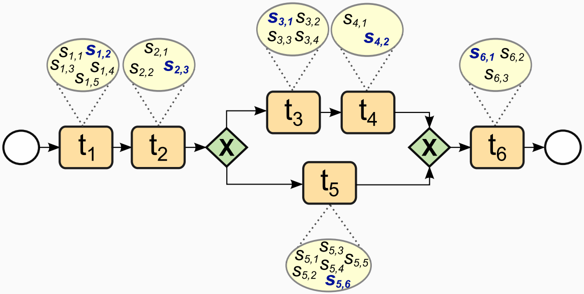
QoS Properties

Table 1: Utility functions

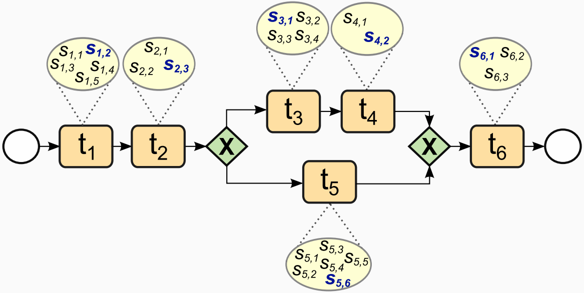
QoS property	*Sequence*	*Loop*	*Branch*	*Fork*
Response time (T)	$\sum_{i=1}^{m} T(a_i)$	$k \cdot \sum_{i=1}^{n} T(a_i)$	$\sum_{i=1}^{m} P_i \cdot T(s_i^b)$	$\min_{i=1}^{p} T(s_i^f)$
Availability (A)	$\prod_{i=1}^{m} A(a_i)$	$(\prod_{i=1}^{n} A(a_i))^k$	$\sum_{i=1}^{m} P_i \cdot A(s_i^b)$	$\prod_{i=1}^{p} A(s_i^f)$
Reliability (R)	$\prod_{i=1}^{m} R(a_i)$	$(\prod_{i=1}^{n} R(a_i))^k$	$\sum_{i=1}^{m} P_i \cdot R(s_i^b)$	$\min_{i=1}^{p} R(s_i^f)$
Throughput (G)	$\min_{i=1}^{m} G(a_i)$	$\min_{i=1}^{m} G(a_i)/k$	$\sum_{i=1}^{m} P_i \cdot G(s_i^b)$	$\min_{i=1}^{p} G(s_i^f)$
Latency (L)	$\sum_{i=1}^{m} L(a_i)$	$k \cdot \sum_{i=1}^{n} L(a_i)$	$\sum_{i=1}^{m} P_i \cdot L(s_i^b)$	$\min_{i=1}^{p} L(s_i^f)$
Successability (U)	$\prod_{i=1}^{m} U(a_i)$	$(\prod_{i=1}^{n} U(a_i))^k$	$\sum_{i=1}^{m} P_i \cdot U(s_i^b)$	$\sum_{i=1}^{p} U_i \cdot U(s_i^f)$
Compliance (C)	$(\sum_{i=1}^{m} C(a_i))/n$	$(\sum_{i=1}^{m} C(a_i))/n$	$\sum_{i=1}^{m} P_i \cdot C(s_i^b)$	$(\sum_{i=1}^{m} C(a_i))/n$
Best practices (B)	$(\sum_{i=1}^{m} B(a_i))/n$	$(\sum_{i=1}^{m} B(a_i))/n$	$\sum_{i=1}^{m} P_i \cdot B(s_i^b)$	$(\sum_{i=1}^{m} B(a_i))/n$
Documentation (D)	$(\sum_{i=1}^{m} D(a_i))/n$	$(\sum_{i=1}^{m} D(a_i))/n$	$(\sum_{i=1}^{m} D(s_i^b))/n$	$(\sum_{i=1}^{p} D(s_i^f))/n$

Optimisation model

Solution encoding



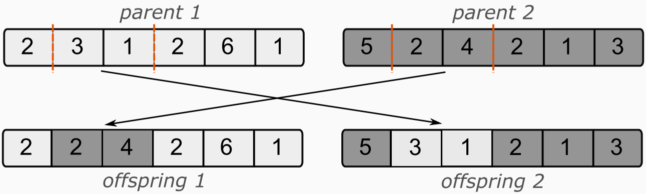
Solution encoding



t_1	t_2	t_3	t_4	t_5	t_6
2	3	1	2	6	1

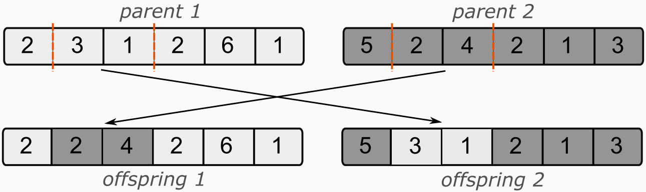
Genetic operators

Crossover

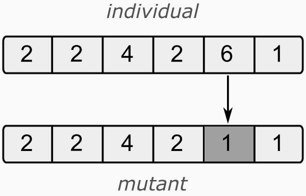


Genetic operators

Crossover



Mutation



Multi/Many-objective evolutionary algorithms

Eight algorithms from five different families are compared:

- Pareto-based: SPEA2, NSGA-II
- Decomposition: MOEA/D
- Reference-set: NSGA-III
- Landscape partition: ϵ-MOEA, GrEA
- Indicator-based: IBEA, HypE

Experimental framework and results

Experiment rationale

Experiment #1: 15 instances. This experiment aims to identify which algorithm performs better (with different sizes of the search space).

- Number of tasks: 10, 20, 30, 40, 50 (a workflow each)
- Number of services: randomly chosen per service between 1-11 (3 x)

Experiment #2: 45 instances. This experiment aims to ensure that the results of Experiment #1 are robust with respect to the variability in the composition structure (workflow).

- Number of tasks: 10, 30, 50
- Number of workflows of each size: 15

Additional material: `http://www.uco.es/grupos/kdis/sbse/RPRSR15`

Statistical validation in terms of two quality indicators: hypervolume (HV) and spacing (S)

Table 2: Hypervolume

i	*Algorithm*	*Ranking (Friedman)*	α/i *(Holm)*
7	NSGA-III	8.0000	0.0071
6	SPEA2	6.1333	0.0083
5	GrEA	6.0000	0.0100
4	MOEA/D	4.8000	0.0125
3	IBEA	4.2667	0.0167
2	NSGA-II	3.4000	0.0250
1	HypE	2.0000	0.0500
0	ϵ-MOEA	1.4000	

Table 3: Spacing

i	*Algorithm*	*Ranking (Friedman)*	α/i *(Holm)*
7	IBEA	8.0000	0.0071
6	HypE	6.5333	0.0083
5	GrEA	6.4000	0.0100
4	NSGA-III	4.7333	0.0125
3	ϵ-MOEA	4.0000	0.0167
2	SPEA2	2.7333	0.0250
1	MOEA/D	2.6000	0.0500
0	NSGA-II	1.0000	

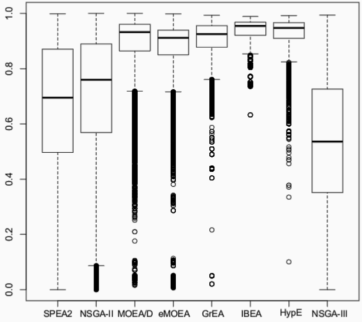
Results – Experiment #1

Table 4: Best algorithms for each QoS property (percentages)

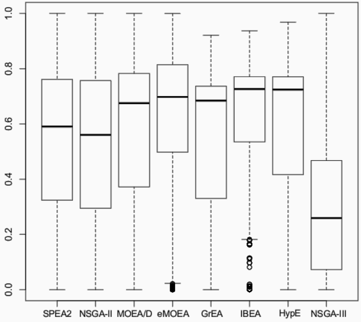
QoS Property	SPEA2	NSGA-II	MOEA/D	ϵ-MOEA	GrEA	IBEA	HypE	NSGA-III
Response time (T)	0.00	0.00	0.00	0.00	6.67	53.33	40.00	0.00
Availability (A)	0.00	6.67	0.00	13.33	0.00	40.00	40.00	0.00
Reliability (R)	0.00	0.00	0.00	13.33	0.00	6.67	80.00	0.00
Throughput (G)	0.00	0.00	0.00	13.33	0.00	6.67	80.00	0.00
Latency (L)	0.00	0.00	0.00	0.00	0.00	33.33	66.67	0.00
Successability (U)	0.00	0.00	0.00	6.67	0.00	40.00	53.33	0.00
Compliance (C)	0.00	0.00	0.00	6.67	13.33	26.67	53.33	0.00
Best practices (B)	13.33	0.00	6.67	40.00	0.00	20.00	20.00	0.00
Documentation (D)	0.00	0.00	0.00	33.33	6.67	40.00	20.00	0.00

Results – Experiment #1

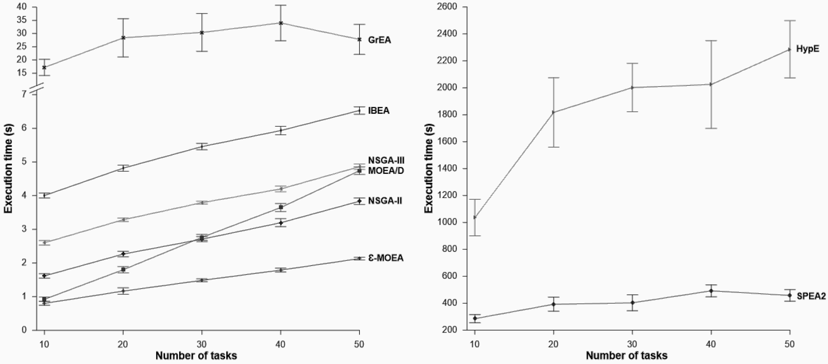
Response time



Best practices



Scalability in terms of number of tasks



(NSGA-II, MOEA/D, ε-MOEA, GrEA, IBEA, NSGA-III)

(SPEA2, HyPE)

Results – Experiment #2

With a larger number of problem instances, the outcomes confirm previous findings:

- Similar ranking positions regarding the quality indicators.
- HypE is the best algorithm for the 6 runtime properties.
- ϵ-MOEA and IBEA provide better values for design properties.
- The workflow does not affect the relative performance.

Conclusions

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Most important insights:

- Suitability of multi- and many-objective approaches.
- Analysis of the factors that can influence the performance.
- Ability of certain many-objective algorithms to optimise specific QoS properties.

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Most important insights:

- Suitability of multi- and many-objective approaches.
- Analysis of the factors that can influence the performance.
- Ability of certain many-objective algorithms to optimise specific QoS properties.

Areas to be explored:

- Extension of the problem formulation: constraints, dependencies...
- Integration of preference information and prioritisation techniques.
- Combining solutions at design time and runtime.
- Application to real case studies.

Thank you for your attention!

Questions?

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