A parallel hybrid evolutionary algorithm for the optimization of broker virtual machines subletting in cloud systems

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Contents

1. Introduction
2. The Virtual Machine Mapping Problem (VMMP)
3. Literature review
4. A parallel hybrid evolutionary algorithm for the VMPP
5. Experimental analysis
6. Conclusions and future work

Introduction

Cloud computing

- Emerged as a powerful computing paradigm due to elasticity, flexibility, and large computational power
- Extends the concept of utility computing, coined in the late 1990s
  - Computing resources as on-demand services
- Offers many services (hardware, software, networking) in several levels

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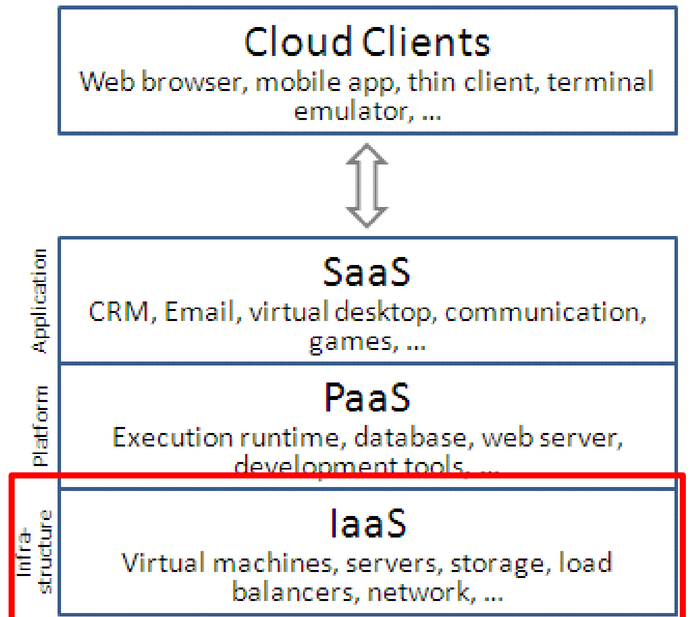
- We focus on the Infrastructure as a Service (IaaS) paradigm
  - Offers computing and storage services
  - Based on virtual machines (VMs)



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  - Booked instances (cheaper, 12 to 24 months required)

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- New agent: the *broker*
  - owns a set of VMs (*reserved instances, RI*) with different features
  - sublets on-demand resources at cheaper prices than the customer would get from a cloud provider
  - if not enough VMs for customer requests without violating SLA, the broker buys on-demand VMs to satisfy the users, and his profit is reduced (he pays more than what he charges the customer for that VM)

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This work presents a parallel hybrid evolutionary algorithm for allocating the customers' VM requests into the available RIs from the broker, maximizing the profit

The Virtual Machine Mapping Problem

Formulation

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$$\max \sum_{j=1}^{j=m} \left(\sum_{i:f(v_i)=b_j} (p(BF(v_i)) - C(b_j)) \times T(v_i) \right) + \sum_{h:ST(v_h)>D(v_h)} (p(BF(v_h)) - COD(BF(v_h))) \times T(v_h)$$

subject to $M(v_i) \leq M(b_j),\ P(v_i) \leq P(b_j)$
$S(v_i) \leq S(b_j),\ nc(v_i) \leq nc(b_j)$

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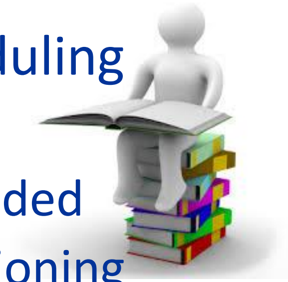

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- Wu et al. (2008): encourage customers to provide realistic resource utilization, with price reduction rewards
  - Forecast required resources, minimizing underutilization/overbooking
  - Benefits the customer too: service at a low price
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Our approach: how the broker can manage VMs for maximizing profit and QoS, by using on-demand instances to fulfill the needs of users that cannot be satisfied with current resources, despite the money loss

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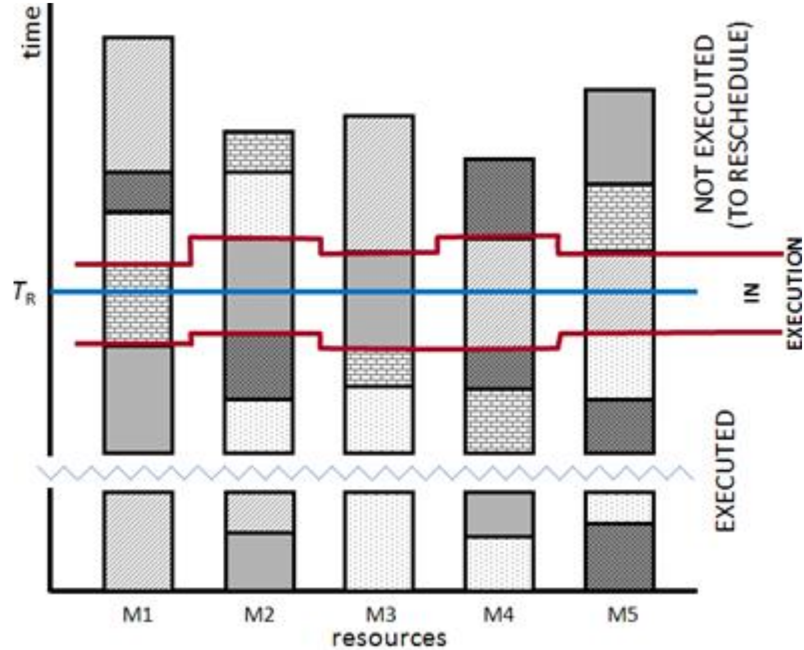
- Rescheduling strategy: find a new schedule for executing the incoming requests (in each new batch) and those submitted requests that have not been executed yet
  - In each rescheduling, the cost takes into account the remaining time of those VM requests already in execution at time T_R in each RI
  - To model this situation, at time T_R each pre-booked instance has an available start time AS(b_i)



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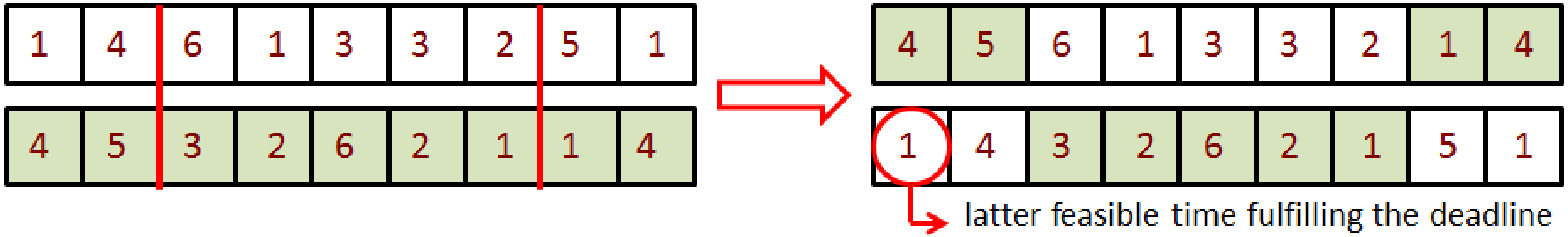

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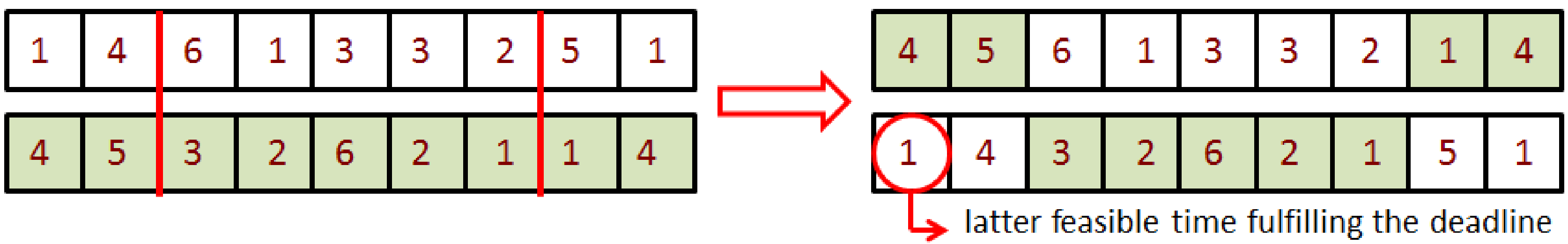

  - *Mutation*: with a low probability a VM request is rescheduled to execute on a randomly selected RI on a random position in the scheduling queue
    - If the (rescheduled) starting time satisfies the deadline requirement, the request is rescheduled. Otherwise, the mutation is discarded

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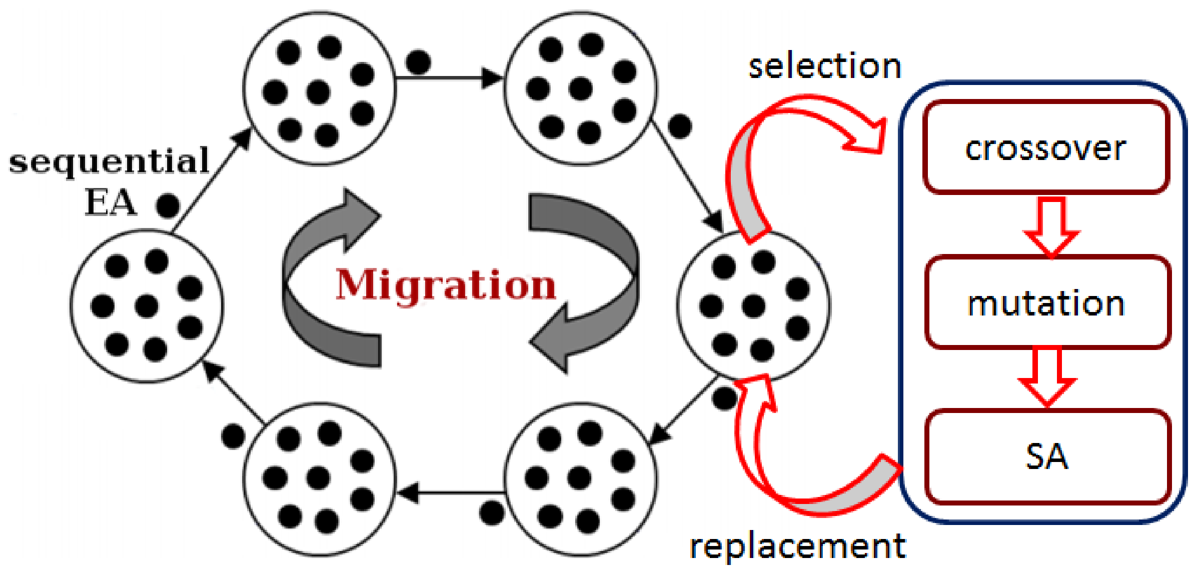
  - connected on a directed-ring topology. Each subpopulation collaborates with adjacent neighbors subpopulation using a migration operator



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- *scenarios*: broker RIs, costs (prebooked/on-demand) and pricing values
  - 10 to 50 RIs, VMs from Amazon and Azure cloud services
  - Pricing function: 20% cheaper than the on-demand price. Reasonable value for attracting users to the service and obtaining interest profit

#	VM id	provider	memory	storage	proc.	nc	price	C	COD
1	m1.small	Amazon	1.7 GB	160 GB	1.0 GHz	1	0.048	0.027	0.06
2	m1.medium	Amazon	3.75 GB	410 GB	2.0 GHz	2	0.096	0.054	0.12
3	A2.medium	Azure	3.5 GB	489 GB	1.6 GHz	2	0.096	0.09	0.12
4	m1.large	Amazon	7.5 GB	850 GB	2.0 GHz	4	0.192	0.108	0.24
5	m2.xlarge	Amazon	17.1 GB	420 GB	3.25 GHz	2	0.192	0.136	0.24
6	A3.large	Azure	7.0 GB	999 GB	1.6 GHz	4	0.328	0.18	0.41
7	c1.xlarge	Amazon	7.0 GB	1690 GB	2.5 GHz	8	0.384	0.316	0.48
8	A4.xlarge	Azure	14.0 GB	2039 GB	1.6 GHz	8	0.464	0.36	0.58

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- Development and execution platform
  - AMD Opteron 6172, 24 core, 2.1GHz, 24GB RAM, Cluster FING: http://www.fing.edu.uy/cluster

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  - 30 independent executions for each of the 27 parameter combinations
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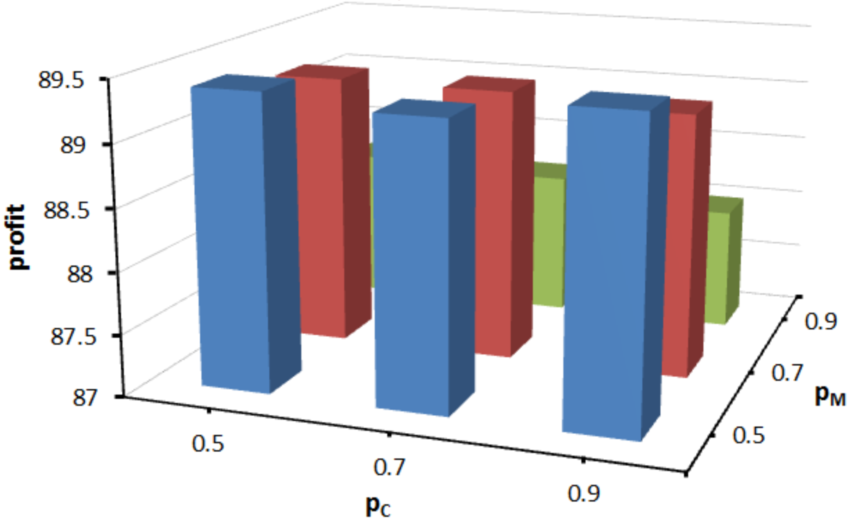
- Post-hoc analysis of the FRS results: the most accurate schedules were computed when using p_C=0.7, p_M=0.5, and p_{SA}=0.3



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  - Cheapest Instance (CI) and Shortest Resource Cheapest Instance (SRCI) from previous work (Nesmachnow et al. 2013)
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dimension	**profit improvement**			**makespan gap**		**violations**
	best	*avg.*	*#1*	*CI*	*SRCI*	*avg.*
50×10	133.8%	43.3%	25/25	16.3%	17.7%	2.7%
100×20	47.7%	17.8%	25/25	14.1%	10.0%	2.5%
200×20	46.2%	28.7%	25/25	8.7%	5.4%	9.7%
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	best	*avg.*	*#1*	*CI*	*SRCI*	*avg.*
50×10	133.8%	43.3%	$^{25}/_{25}$	16.3%	17.7%	2.7%
100×20	47.7%	17.8%	$^{25}/_{25}$	14.1%	10.0%	2.5%
200×20	46.2%	28.7%	$^{25}/_{25}$	8.7%	5.4%	9.7%
400×50	63.7%	26.3%	$^{25}/_{25}$	9.0%	4.5%	5.5%

Results and discussion

- EA+SA compared against greedy list-scheduling heuristics:
  - Cheapest Instance (CI) and Shortest Resource Cheapest Instance (SRCI) from previous work (Nesmachnow et al. 2013)
- 50 independent executions on each VMMP instance
- Evaluate the *gap* metric with respect to each heuristic H:

improved schedules

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few deadline violations

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Parallelism

- Contribution of the parallel model to the results quality

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dimension	average profit improvement		
	1 deme	*8 demes*	*24 demes*
50×10	$42.89\pm0.39\%$	$43.20\pm0.16\%$	$43.29\pm0.09\%$
100×20	$17.09\pm0.52\%$	$17.60\pm0.31\%$	$17.80\pm0.20\%$
200×20	$24.83\pm1.36\%$	$27.57\pm0.91\%$	$28.71\pm0.75\%$
400×50	$21.34\pm2.04\%$	$24.57\pm1.44\%$	$26.30\pm1.23\%$

Experimental analysis

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- Contribution of the parallel model to the results quality

dimension	average profit improvement		
	1 deme	*8 demes*	*24 demes*
50×10	42.89±0.39%	43.20±0.16%	43.29±0.09%
100×20	17.09±0.52%	17.60±0.31%	17.80±0.20%
200×20	24.83±1.36%	27.57±0.91%	28.71±0.75%
400×50	21.34±2.04%	24.57±1.44%	26.30±1.23%

- Using 24 demes account for an additional 5% on the profit results over the sequential search

Conclusions and future work

Parallel EA+SA for the Virtual Machine Mapping Problem

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- A parallel optimization algorithm is proposed for brokering scheduling
  - Combines EA and SA in a weak hybrid method

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Parallel EA+SA for the Virtual Machine Mapping Problem

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- Studied the problem of virtual machines subletting in cloud systems
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  - EA+SA allows tackling large problem instances in reduced execution times
  - Clearly outperform the best existing results in the literature: the broker profit is increased by 18% (average) and up to 133.8% (best)
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  - Scalability analysis: profit improves when using parallelism, particularly for the biggest problem instances
- Future work:
  - Further analyze the behavior/dynamics of the new scheduling method
  - Designing an accurate forecasting technique to predict the resources the broker will need in the future

THANKS FOR YOUR ATTENTION

FACULTAD DE INGENIERÍA, UNIVERSIDAD DE LA REPÚBLICA, URUGUAY