EXAMPLE 2018 Machine learning for a 50 future Machine Learning Opportunities in Cloud Computing Datacenter Management for 5G Services

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- Introduction and Motivation
- Two-Phase Optimization Scheme for VMP Problems
- Machine Learning Opportunities
- Conclusions and Future Directions



- 5G networks and services will increase exponentially in data traffic, storage and processing.
- Smartphones as gateways to remotely access resources through cloud computing.
- Several challenges should be addressed to further advance cloud computing in order to serve as a basis to integrate 5G components and protocols.
- For cloud computing datacenters, main research challenges could be addressed by designing management solutions based on Machine Learning (ML) techniques.





- Large-scale infrastructures providing computational services.
- Energy consumption, carbon emissions, among others.
- Quality of Service
 - High availability
 - Security
 - ..
- Resource Management
 - Resource Allocation
 - Resource Adaptation



Google's Datacenter [www.google.com/about/datacenters]





Virtual Machine Placement (VMP)

Which virtual machines should be located at each physical machine?

Virtual Machines (VMs)



Physical Machines (PMs)





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 VMP for Cloud Computing under uncertainty: Provider-oriented VMP in Federated-Cloud Deployments.



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VMP for Cloud Computing under uncertainty:

MAM Optimization, Heuristics + Meta-Heuristics and Multiple Objectives.

Technique	Approach	Objective Functions				
rechnique	Approach	$f_1(x)$	$f_2(x)$	$f_3(x)$	$f_4(x)$	$f_5(x)$
Deterministic	MOP	[53]	[114]	[30]	[15]	[84]
Algorithms	MAM	[6, 131]	[6, 129]	RO	RO	[129, 131]
Aigoriinnis	PMO	RO	RO	RO	RO	RO
	MOP	[39]	[33]	[125]	[55]	[84]
Heuristics	MAM	[37, 121]	[37, 61]	[29, 61]	[121, 146]	[20, 21]
	PMO	RO	RO	RO	RO	RO
Meta-	MOP	[135]	RO	[105]	[142]	RO
Heuristics	MAM	[26, 150]	[26, 126]	[1, 150]	[126]	[1, 150]
1104/131103	РМО	[51, 89]	[89, 100]	[89, 100]	RO	[51]
Approximation	MOP	[148]	RO	RO	RO	RO
Approximation Algorithms	MAM	[43]	RO	RO	RO	RO
Лідот шті	PMO	RO	RO	RO	RO	RO





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Deployment Models

Private cloud
 Community cloud
 Public cloud
 Hybrid cloud

Cloud computing is a **model** for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction. This cloud model is composed of **5** essential characteristics, **3** service models, and **4** deployment models [107].

26-28 November Santa Fe, Argentina [107] Mell and Grance. "The NIST definition of Cloud Computing", 2011.





- Placement of Cloud Services, mostly composed by more than just one VM towards a Software-Defined Datacenter.
- Consider relevant characteristics of Infrastructure as a Service model of Cloud Computing for the VMP problem such us:
 - On-Demand Self-Service
 - Rapid Elasticity

(dynamic) (dynamic)

- Most relevant dynamic parameters in VMP problems are [112]:
 - Resource Capacities of VMs
 - Number of VMs of a Cloud Service
 - Utilization of Resources of VMs

(vertical elasticity) (horizontal elasticity) (overbooking)

26-28 November Santa Fe, Argentina [112] Ortigoza, López-Pires and Barán. "A Taxonomy on Dynamic Environments for provider-oriented Virtual Machine Placement" in IC2E



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 IaaS environments for provider-oriented VMP problems could be classified by one or more of the following classification criteria [112]:

Elasticity	Overbooking
0. no elasticity	0. no overbooking
1. horizontal elasticity	1. server resources overbooking
2. vertical elasticity	2. network resources overbooking
3. both horizontal and vertical elasticity	3. both server and network overbooking

• The are 16 possible VMP environments for Cloud Computing.

26-28 November Santa Fe, Argentina [112] Ortigoza, López-Pires and Barán. "A Taxonomy on Dynamic Environments for provider-oriented Virtual Machine Placement" in IC2E



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- A VMP problem formulation for the optimization of:
 - 1. Power Consumption
 - 2. Economical Revenue
 - 3. Quality of Service
 - 4. Resource Utilization



- Online Algorithms: Heuristics
- Offline Algorithms: Meta-Heuristics







(Online) A1: First-Fit	(Online) A4: First-Fit Decreasing
(Online) A2: Best-Fit	(Online) A5: Best-Fit Decreasing
(Online) A3: Worst-Fit	(Offline) A6: Memetic Algorithm

Table	Table 5.2: Objective Function Costs of Evaluated Algorithms.					
Algorithm Workload	A1: FF	A2: BF	A3: WF	A4: FFD	A5: BFD	A6: MA
W_1 : Poisson $\lambda = 10$	3.2927	3.3098	3.5250	3.0205	3.1392	2.6096
W_2 : Poisson $\lambda = 50$	2.4602	2.5112	2.4811	2.4602	2.4555	2.0001
W_3 : Poisson $\lambda = 70$	1.7054	1.6458	1.7054	1.6458	1.6458	1.3588
W_4 : Uniform	3.1875	3.1556	3.0489	3.0907	3.1556	2.3420
Average	2.6615	2.6556	2.6901	2.5543	2.5990	2.0776
Ranking	5th	4th	6th	2nd	3th	1st

m 11 A 1 14.1 а.



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A 1 14.1 1 1



Algorithm	Advantages	Disadvantages	
offline meta- heuristic (A6)	 better quality of solutions when comparing to online alternatives. 	 not appropriate for highly dynamic environments of VMP problems- 	
online heuristics (A1 – A5)	 short execution time unknown cloud service requests are considered. 	 online decisions negatively affects the quality of solutions. 	



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IaaS environments for provider-oriented VMP problems





IaaS environments for provider-oriented VMP problems



26-28 November [156] Zheng, et al. "Virtual machine placement based on multi-objective Santa Fe, Argentina biogeography-based optimization" in Future Generation Computer Systems, 2015.

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- A VMP problem formulation for the optimization of:
 - **Power Consumption** 1.
 - 2. **Economical Revenue**
 - 3. **Resource Utilization**
 - **Reconfiguration Time** 4.



- Uncertain parameters considered:
 - Virtual resources capacities 1.
 - 2. Number of VMs in cloud services
 - Utilization of virtual CPU / RAM 3.
 - Utilization of networking virtual 4.

(vertical elasticity) (horizontal elasticity) (server overbooking) (network overbooking)



26-28 November



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Figure 1: Two-phase optimization scheme for VMP problems considered in this work, presenting a basic example with a placement recalculation time of $\beta = 2$ (from t = 2 to t = 4) and a placement reconfiguration time of $\gamma = 1$ (from t = 4 to t = 5).



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when or under which circumstances the VMPr phase should be



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what should be done with cloud service requests arriving during recalculation time?



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Reference	Overbooking Type	Elasticity Type	VMPr Triggering	VMPr Recovering
[20]	CPU	Not Considered	Periodically	Cancellation
[151]	Not Considered	Not Considered	Periodically	Not Considered
[46]	Not Considered	Not Considered	Periodically	Not Considered
[87]	Not Considered	Not Considered	Periodically	Not Considered
[44]	CPU and RAM	Not Considered	Periodically	Not Considered
[156]	Not Considered	Not Considered	Periodically	Not Considered
[132]	Not Considered	Not Considered	Continuously	Not Considered
[13]	CPU	Not Considered	Threshold-based	N/A
[123]	CPU, RAM and Network	Not Considered	Threshold-based	N/A
[137]	CPU	Horizontal	Threshold-based	N/A
This work	CPU, RAM and Network	Vertical and Horizontal	Prediction-based	Update-based



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A contribution:

A novel prediction-based VMPr Triggering method to decide when or under what circumstances the VMPr phase should be triggered.



- Considers main weaknesses of existing VMPr Triggering methods.
- Considers Double Exponential Smoothing (DES) [63] as a statistical technique for predicting values of the objective functions.
- Predicts the next values of objective functions and triggers the VMPr phase in case objectives are predicted to consistently increase (in a minimization context).

26-28 November [63] Huang et al. "Resource prediction based on double exponential smoothing Santa Fe, Argentina in cloud computing" in CECNet 2012.



• ML for VMPr Triggering:

- RQ 1: which ML techniques could be considered more appropriate for VMPr Triggering methods?
- RQ 2: how important is to accurately predict when to trigger a VMPr phase in VMP problems?
- RQ 3: rather than predicting future objective function values, what other parameters could be evaluated for VMPr Triggering methods?



• ML for Network Management:

- RQ 4: which ML techniques could be considered more appropriate for predicting Network Routing Reconfiguration (NRR) as part of VMP problems in SDN implementations?
- RQ 5: which ML techniques could be considered more appropriate for clustering VMs for supporting placement decisions?



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Thank you