Institut Mines-Télécom

Futur & Ruptures a 10 ANS ! 2008-2018

FONDATION Mines-Télécom La Fondation de l'IMT

INSTITUT CARNOT Télécom & Société numérique

# GENERIC AUTONOMIC SERVICE MANAGEMENT IN COMPLEX SYSTEMS


PhD candidate:

Nabila Belhaj*

Advisors:

Djamel Belaïd*

Samir Tata†

*CNRS/SAMOVAR, Telecom SudParis

† Almaden Research Center, IBM Research, San Jose, CA, USA

Institut Mines-Télécom

Futur & Ruptures a 10 ANS ! 2008-2018

FONDATION Mines-Télécom La Fondation de l'IMT

INSTITUT CARNOT Télécom & Société numérique

# GENERIC AUTONOMIC SERVICE MANAGEMENT IN COMPLEX SYSTEMS

IMT Atlantique Bretagne-Pays de la Loire École Mines-Télécom

IMT Lille Douai École Mines-Télécom IMT-Université de Lille

IMT Mines Albi-Carmaux École Mines-Télécom

IMT Mines Alès École Mines-Télécom

MINES Saint-Étienne Une école de l'IMT

TELECOM Management Une école de l'IMT

TELECOM ParisTech Une école de l'IMT

TELECOM SudParis Une école de l'IMT

EURECOM

MINES ParisTech

MINESnancy

ARMINES

# AGENDA



Institut Mines-Télécom

# INTRODUCTION

1.1. CONTEXT

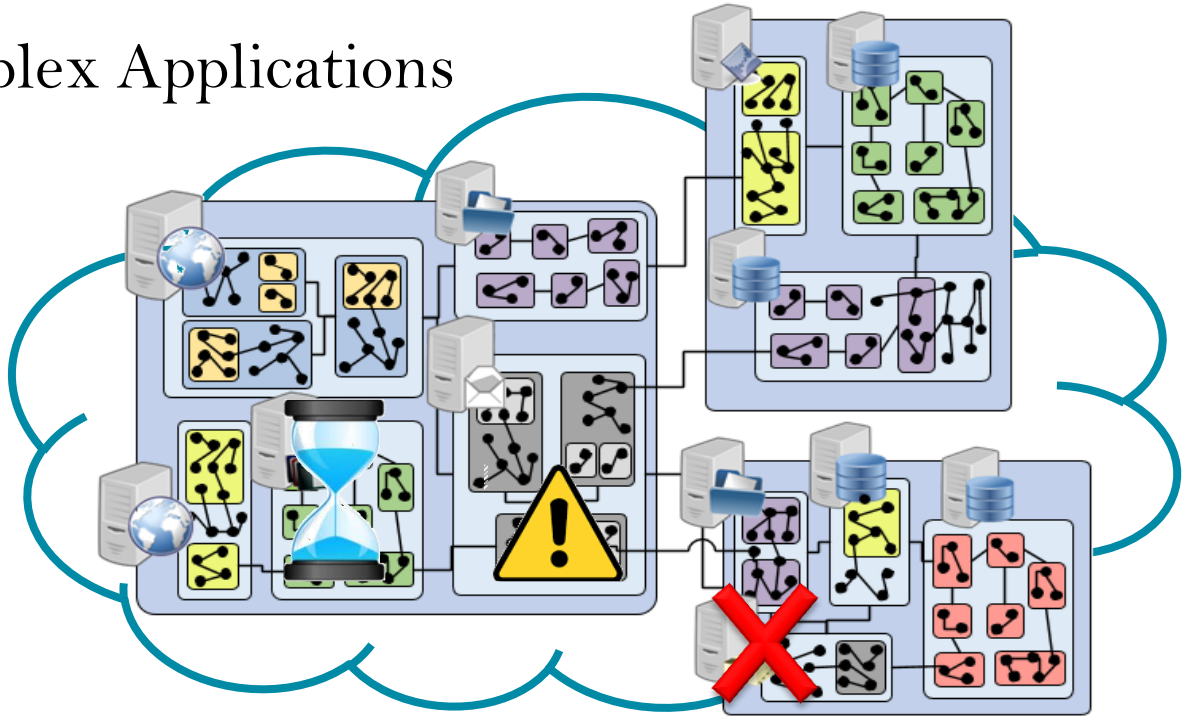
1.2. CONTRIBUTION OBJECTIVES

1.3. RELATED WORK

Institut Mines-Télécom

# CONTEXT

- Complex Applications



Corrective Actions

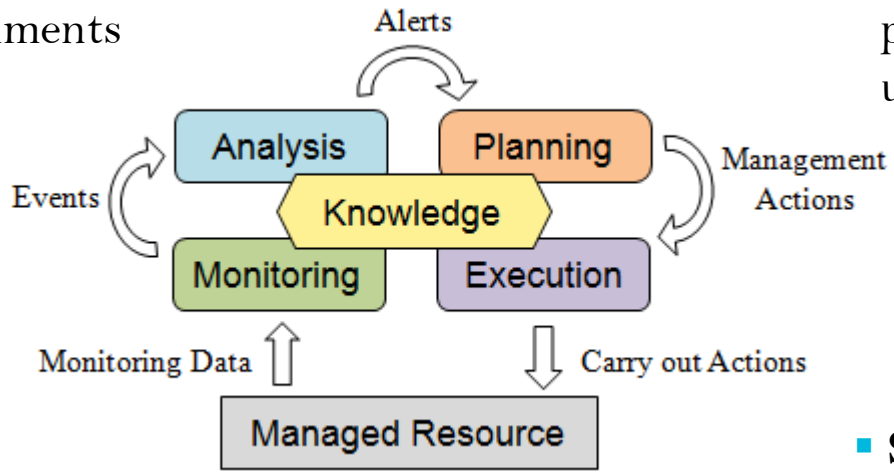
- Complex structure and increasing size
- Heterogeneous composition of distributed and interracting components
- Highly dynamic deployment contexts
- Tedious management tasks

# CONTEXT

## Autonomic Computing Systems (ACS): Self-properties

- **Self-Reconfiguring**
  Adapting itself to changing environments "on the fly".

- **Self-Optimizing**
  Optimizing system performance and resource utilization.




- **Self-Healing**
  Discovering, diagnosing and acting for disruption prevention.

- **Self-Protecting**
  Identifying and anticipating unauthorized accesses to protect from attacks.

**Sophisticated ACS knowledge-based systems learn from their past experience and make strategic decisions**

**Extended ACS knowledge-based systems learn from dynamic context and make tactical decisions**

# CONTRIBUTION OBJECTIVES



1. Enhance traditional ACS with sophisticated learning behavior
2. Render self-adaptive the decision making for component-based applications
3. Optimization of learning performance
4. Make autonomic loops collaborate for a consistent decision making in the overall system

# RELATED WORK



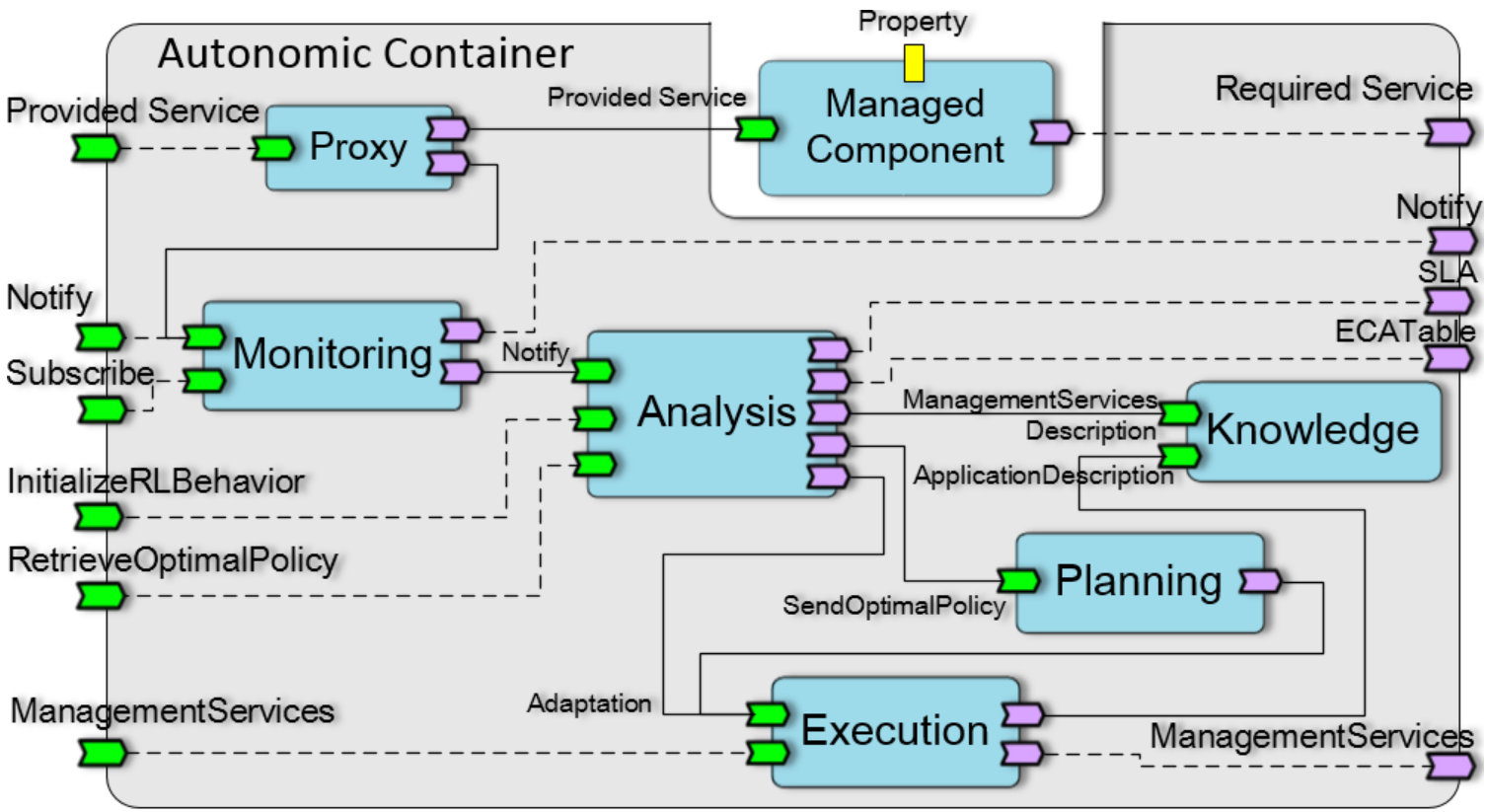
| Approaches | Assessment criteria | | | |
|---|---|---|---|---|
| | 1. Enhancement of MAPE-K behavior | 2. Dynamic decision policy | 3. Optimization of learning performance | 4. Richer context |
| Raghavendra, R. et al., 2008 | - | - | - | - |
| Gueye, S.M.K. et al., 2013 | - | - | - | - |
| Cano, J. et al., 2013 | - | - | - | - |
| Li, Z., Parashar, M, 2005 | - | - | - | - |
| Tesauro, G.,2007 | - | X | - | - |
| Rao, J. et al., 2011 | - | X | - | - |
| Wang, H. et al., 2011 | - | X | - | - |
| Wang, H. et al., 2016 | - | X | - | X |
| **Our proposal** | X | X | X | X |

# CONTRIBUTIONS



Institut Mines-Télécom

- Structure of the Autonomic Container

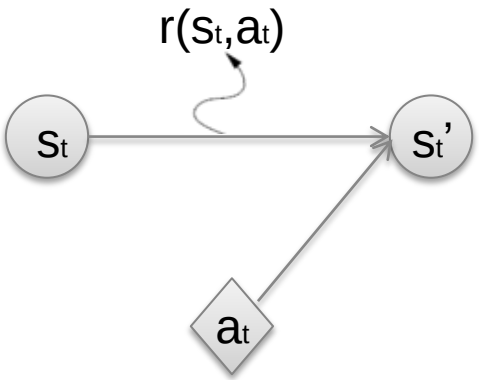


# BACKGROUND: REINFORCEMENT LEARNING (RL)

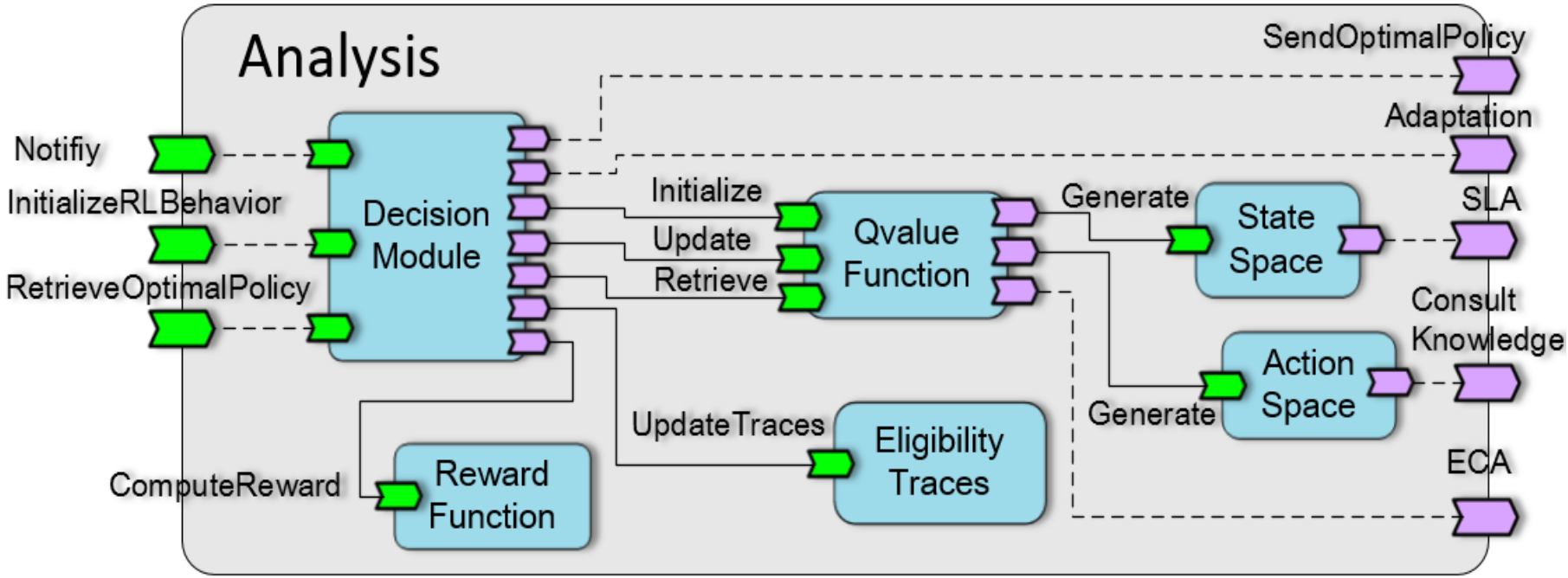


- **Main goal:**
  Find the optimal decision policy that maximizes the long-run sum of reward signals.


- **Markov Decision Process (MDP):**
  - S: finite set of states,
  - A: finite set of actions,
  - P( ): transition probability between states
  - R( ): reward function on state transitions



- Structure of the Analysis component



# MAPPING DECISION PROCESS TO MDP PROBLEM



- State Space: $S = \{s_i \ / \ s_i = (v_{m_{1i}}, v_{m_{2i}}, .., v_{m_{ji}})\}$

  $v_{m_{ji}}$ : runtime value of metric $m_j$ of $s_i$

  $s_i$ : should comply with $O = \{o_{m_1}, o_{m_2}, .., o_{m_j}\}$

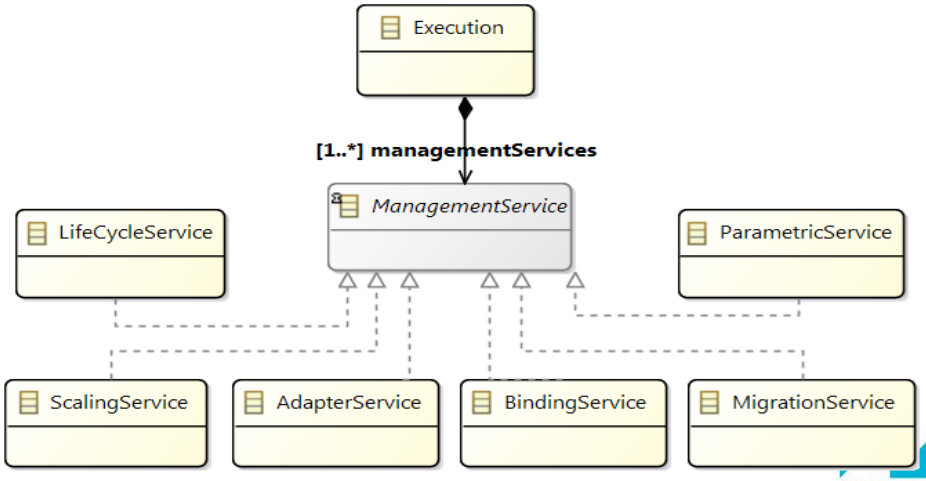
  $o_{m_j}$ : objective value for metric $m_j$

- Action Space: $A = \{A_{el} \cup A_{comp} \cup A_{BPM}\}$

  $A_{el}$ : elementary management service

  $A_{comp}$ : composition of local and/or remote $A_{el}$

  $A_{BPM}$ : orchestration of local and/or remote $A_{el}$



- Reward Function

**Algorithm 1.** Reward Function

1: **Input:** $s_t, s'_t$
2: **for all** metrics values $v'_{m_{1t}}, v'_{m_{2t}}, .., v'_{m_{jt}}$ **do**
3: $$r_{v'_{m_{kt}}} = \begin{cases} 0 & \text{if } v'_{m_{kt}} = o_{m_k} \text{ (border)} \\ d_{v'_{m_{kt}}, o_{m_k}} & \text{if } v'_{m_{kt}} \text{ satisfies } o_{m_k} \text{ (good or best)} \\ -d_{v'_{m_{kt}}, o_{m_k}} & \text{otherwise (bad or worst)} \end{cases}$$
4: **end for**
5: $C_{s'_t} \leftarrow ComplianceDegree(min\{r_{v'_{m_{1t}}}, r_{v'_{m_{2t}}}, .., r_{v'_{m_{jt}}}\})$
6: $r_{s'_t} \leftarrow ComputeReward(C_{s'_t})$
7: do loop in Step 2 for metrics values $v_{m_{1t}}, v_{m_{2t}}, .., v_{m_{jt}}$
8: $C_{s_t} \leftarrow ComplianceDegree(min\{r_{v_{m_{1t}}}, r_{v_{m_{2t}}}, .., r_{v_{m_{jt}}}\})$
9: $r_{(s_t \rightarrow s'_t)} \leftarrow CompareStates(C_{s_t}, C_{s'_t})$
10: $r_t \leftarrow r_{s'_t} + r_{(s_t \rightarrow s'_t)}$
11: *assign* $r_t$ *to couple* $(s_t, a_t)$
12: **Output:** $r_t$

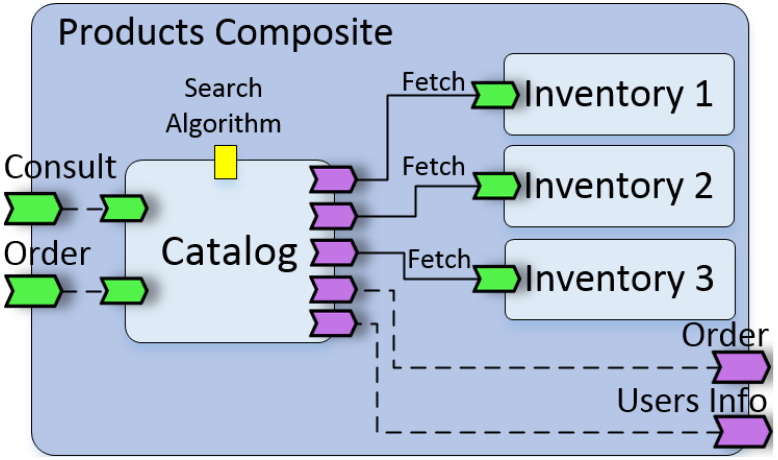
- Online RL decision making

**Algorithm 2.** Learning Decision Process

**Input:** $A, O, ECA, \alpha_0, \gamma, \epsilon, \lambda, \epsilon_z, \xi$
$Initialize(Q_0) \leftarrow Parse(ECA)$
$z_0(s,a) \leftarrow 0, \forall(s,a)$
$\alpha_0(s,a) \leftarrow \alpha_0, \forall(s,a)$
$t \leftarrow 0$
**Repeat:**
$s_t \leftarrow MonitoreCurrentState$
$a_t \leftarrow ChooseAction(s_t)$
$ApplyAction(a_t)$
$s'_t \leftarrow MonitoreCurrentState$
$r_t \leftarrow RewardFunction(s_t, s'_t)$
$\delta_t(s_t, a_t) = r_t + \gamma\ max_b Q_t(s'_t, b) - Q_t(s_t, a_t)$
$z_t(s_t, a_t) = z_t(s_t, a_t) + 1$
Update $Q_t(s,a)$ and $z_t(s,a)$ :
$(S,A)_{M_{transition}} \leftarrow (S,A)_{M_{transition}} \cup \{(s_t, a_t)\} \setminus \{argmin_{(s,a)} z_{(s,a)}\}$
**for all** $(s,a) \in (S,A)_{M_{transition}}$ **do**
    $Q_{t+1}(s,a) \leftarrow Q_t(s,a) + \alpha_t(s,a) z_t(s,a) \delta_t(s_t, a_t)$
    $z_{t+1}(s,a) = \gamma\lambda z_t(s,a)$
**end for**
$\alpha_t \leftarrow Decay(\alpha_t)$
$s_t \leftarrow s'_t$
$t++$
**Until:** All $\alpha\delta \leq \xi$
Return All $Q(s,a)$ and Retrieve $\pi^*$

# USE CASE STUDY

## Shopping Application




```xml
<?xml version="1.0" encoding="UTF-8" ?>
<wsag:AgreementOffer AgreementId="ab97c409">
<wsag:Name>xs:ShoppingApp</wsag:Name>
<wsag:AgreementContext> ... </wsag:AgreementContext>
 <wsag:Terms>
   <wsag:All>
    <wsag:GuaranteeTerm wsag:Name="g1" wsag:Obligated="
        ServiceProvider">
     <wsag:ServiceLevelObjective>
      <wsag:KPITarget>
       <wsag:KPIName>availability_UpTimeRatio</wsag:KPIName>
        <wsag:CustomServiceLevel xmlns:xsi="http://www.w3.org/2001/
            XMLSchema-instance" xmlns:exp="http://www.telecom-
            sudparis.com/exp">
         <exp:Greater><exp:Variable>minthreshold</exp:Variable> <
             exp:Value>0.9</exp:Value></exp:Greater>
        </wsag:CustomServiceLevel>
       <wsag:KPIName>averageResponseTime</wsag:KPIName>
        <wsag:CustomServiceLevel xmlns:xsi="http://www.w3.org/2001/
            XMLSchema-instance" xmlns:exp="http://www.telecom-
            sudparis.com/exp">
         <exp:Less><exp:Variable>maxthreshold</exp:Variable> <
             exp:Value>1200</exp:Value></exp:Less>
        </wsag:CustomServiceLevel>
       <wsag:KPIName>numberServiceCalls</wsag:KPIName>
        <wsag:CustomServiceLevel xmlns:xsi="http://www.w3.org/2001/
            XMLSchema-instance" xmlns:exp="http://www.telecom-
            sudparis.com/exp">
         <exp:Less><exp:Variable>maxthreshold</exp:Variable><
             exp:Value>10</exp:Value></exp:Less>
        </wsag:CustomServiceLevel>
      </wsag:KPITarget>
     </wsag:ServiceLevelObjective>
    ...
    </wsag:GuaranteeTerm>
   </wsag:All>
  </wsag:Terms>
</wsag:AgreementOffer>
```

Metrics objective values:

- $v'_{avai} = true$, 90% of time
- $v'_{resp} \leqslant 1200$ ms
- $v'_{calls} \leqslant 10$

State vector:

$$(v_{avai}, v_{resp}, v_{calls})$$

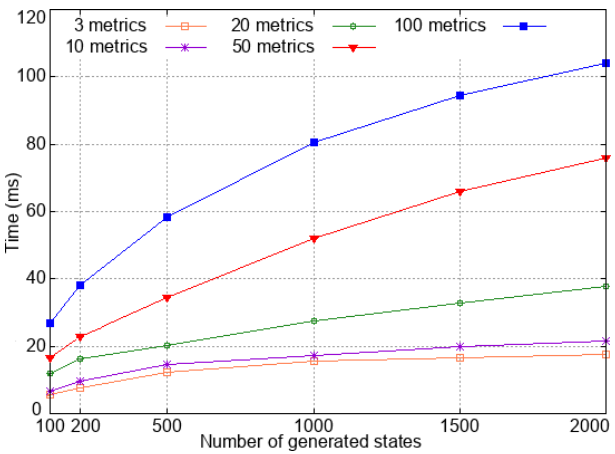
# EVALUATION

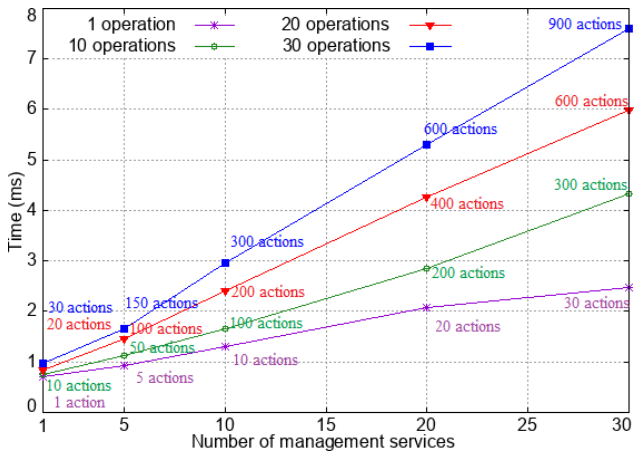


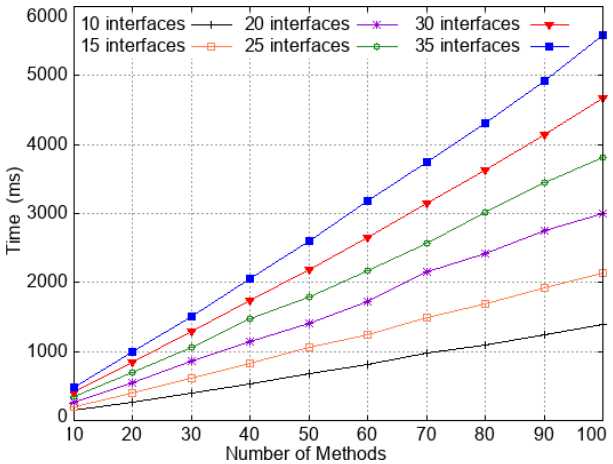
- Evaluation criterion of the Framework
  - Transformation overhead of the application
  - Self-adaptivity to context changes,
  - SLA guarantee,
  - Performance optimization of learning phase
- Context dynamics:
  - Workload (i.e., concurrent service calls) variations:
    - Light, Medium, Heavy
  - Random triggering of service unavailability
- Experiments:
  - One-step online learning
  - Multi-step online learning

# EVALUATION

- Transformation overhead of the application

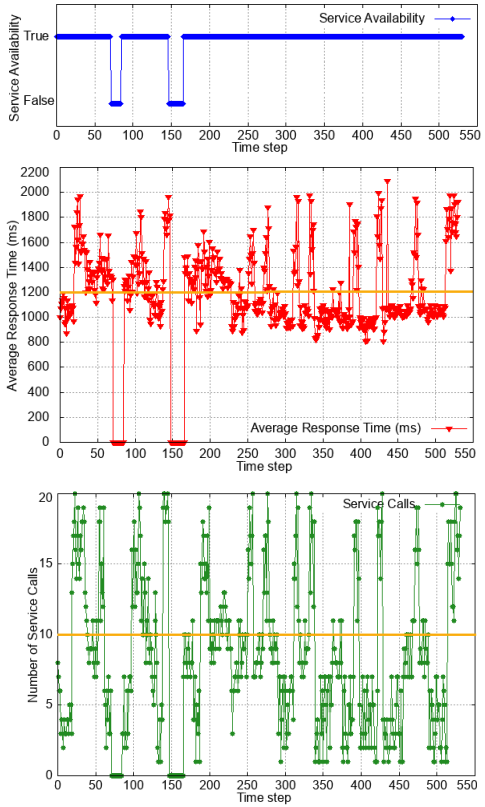


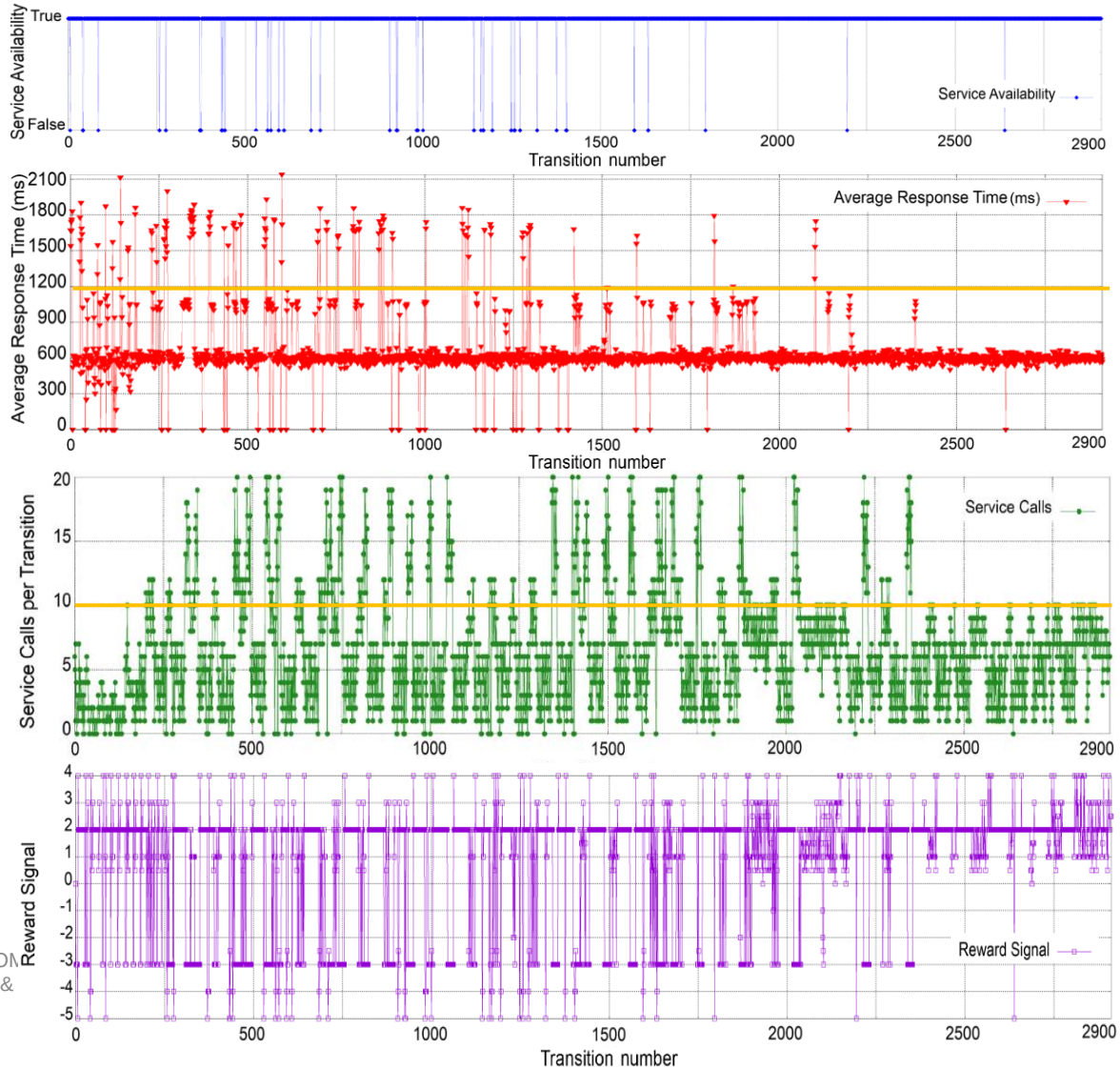



# EVALUATION

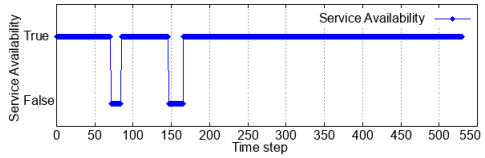
- Self-adaptivity to context changes

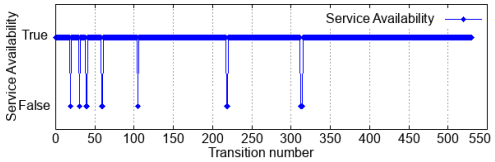


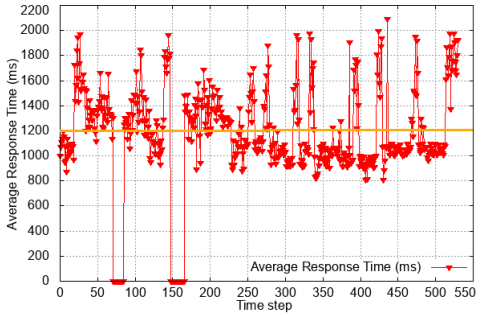



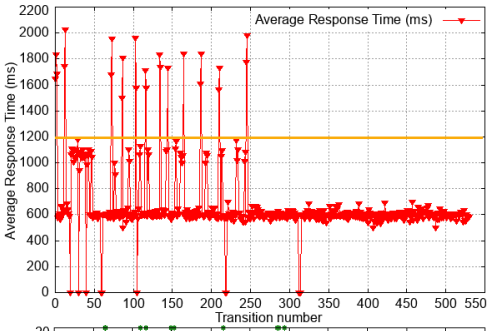
# EVALUATION

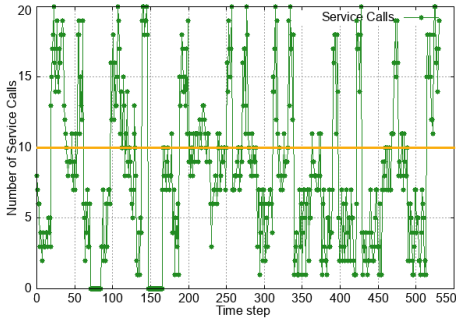
- SLA guarantee and Performance optimization

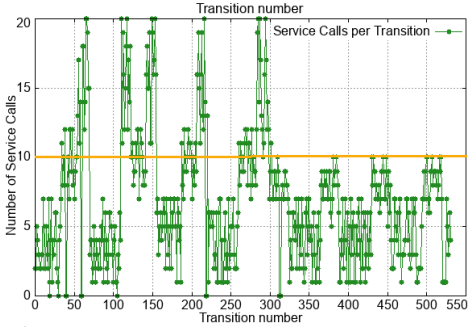


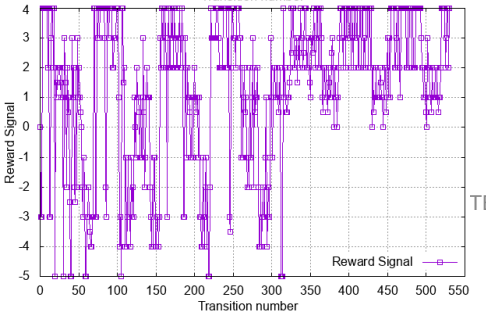



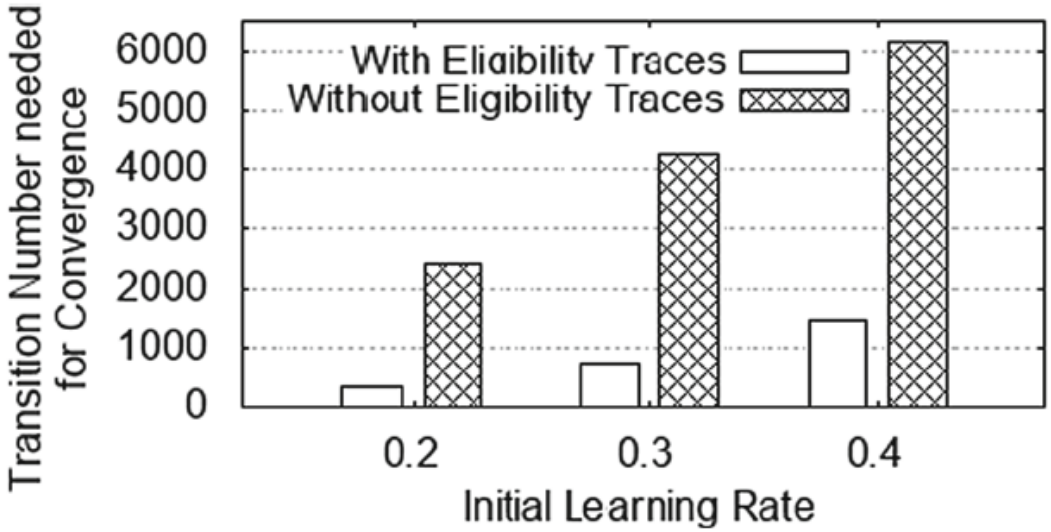



# EVALUATION



- Convergence speed: one-step vs. multi-step online learning



# CONCLUSION AND WORK IN PROGRESS

Institut Mines-Télécom

# CONCLUSION



- Improve the decision making process of a traditional MAPE-K loop
- Replace the common use of inflexible hand-coded strategies for being knowledge-intensive and inadequate to dynamically changing contexts
- Design of sophisticated and better performing autonomic systems that learn based on their past experiences
- Dynamically compute a decision policy that suits the context dynamics

# WORK IN PROGRESS



- Developping collaboration algorithms to make remote autonomic containers collaborate
- Make Analyzes components collaborate for a global consistent learning of decision policies
- Propose mechanisms of conflict detection and conflict resolution for the Analyzes decisions.

Thank you for your attention
Questions are welcome

Institut Mines-Télécom

# PUBLICATIONS



- Published papers:
  - **Nabila Belhaj**, Djamel Belaïd, Hamid Mukhtar, Self-adaptive Decision Making for the Management of Component-Based Applications. In: On The Move, 25rd International Conference on Cooperative Information Systems (CoopIS), Rhodes, Greece, 2017. **A-Rank**.
  - **Nabila Belhaj**, Imen Ben Lahmar, Mohamed Mohamed, Djamel Belaïd, Collaborative Autonomic Management of Distributed Component-Based Applications. In: On The Move, 23rd International Conference on Cooperative Information Systems (CoopIS), Rhodes, Greece, 2015. **A-Rank**.
  - **Nabila Belhaj**, Imen Ben Lahmar, Mohamed Mohamed, Djamel Belaïd, Collaborative Autonomic Container for the Management of Component-Based Applications. In: IEEE 24th International Conference on Enabling Technologies: Infrastructures for Collaborative Enterprises (WETICE), Larnaca, Cyprus, 2015. **B-Rank**.
- Submitted papers:
  - **Nabila Belhaj**, Djamel Belaïd, Hamid Mukhtar, Framework for Building Self-Adaptive Component Applications based on Reinforcement Learning. In: 30th International Conference on Advanced Information Systems Engineering (CAISE), Tallinn, Estonia, 2018. **A-Rank**.