Autonomic Container Elasticity through Reinforcement Learning

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Exploiting Elasticity

- **New scenario**: *IoT edge/fog computing*

- **New software architectures**: *container-based architectures*

- **Common requirement**: *elasticity*

Goal

To adapt at run-time the deployment of container-based applications jointly consider horizontal and vertical scalability.

Solutions proposed in literature:

- threshold-based policies;
- optimization (mainly ILP);
- heuristics;
- control theory;
- time series analysis;
- Reinforcement Learning.

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Main Contributions

Autonomic elasticity of container-based applications:

- Horizontal or Vertical
- Horizontal and Vertical

Reinforcement learning algorithms:

- Q-learning
- Dyna-Q
- Model-based

model-free

model-based

System Definition

- Container-based applications
- Per-application RL agent

- RL agent adapts:
  - number of containers
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For each application, we define:

- $s = (k, u, c)$: application state
- k : number of containers
- u : CPU utilization (discretized)
- c : CPU quota assigned to each container
- a : action carried out in the state s
  - 5 Actions: a in $\{-1, 0, 1, -r, r\}$
  - 9 Actions: a in $\{-1, 0, 1\} \times \{-r, 0, r\}$

Immediate Cost Function

Immediate Cost associated to each triple *(s, a, s')*.

$$
\boxed{\begin{aligned} c(s, a, s') = {} & w_{\mathrm{rcf}} \cdot c_{\mathrm{rcf}} \\ & + w_{\mathrm{perf}} \cdot c_{\mathrm{perf}} \\ & + w_{\mathrm{res}} \cdot c_{\mathrm{res}} \end{aligned}}
$$

Immediate cost defined as the weighted sum of:

- reconfiguration cost;
- performance cost;
- resource cost.

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$$c(s, a, s') = w_{\mathrm{rcf}} \cdot \boxed{c_{\mathrm{rcf}}} + w_{\mathrm{perf}} \cdot \boxed{c_{\mathrm{perf}}} + w_{\mathrm{res}} \cdot \boxed{c_{\mathrm{res}}}$$

c_{rcf}: Vertical scaling operations lead to application unavailability

c_{perf}: Penalty if the application response time violates the SLA

c_{res}: Resource cost, proportional to the amount of allocated resources (k and c)

Reinforcement Learning Algorithms

- $Q(s, a)$: estimate of long-term cost due to the execution of action a in s

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  - action selection policy: ε-greedy

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  - estimates *Q(s, a)* from the experience:

$$Q\left(s_i, a_i\right) \leftarrow (1-\alpha) Q\left(s_i, a_i\right) + \alpha\left[c_i + \gamma \min_{a' \in \mathcal{A}\left(s_{i+1}\right)} Q\left(s_{i+1}, a'\right)\right]$$

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  - same features as Q-learning;

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- **Dyna-Q**
  - same features as Q-learning;
  - mantains a model *(s,a)*$\longrightarrow$*(s', c)*;
  - uses the model to simulate the experience and update *Q(s, a)*.

Model-Based Reinforcement Learning

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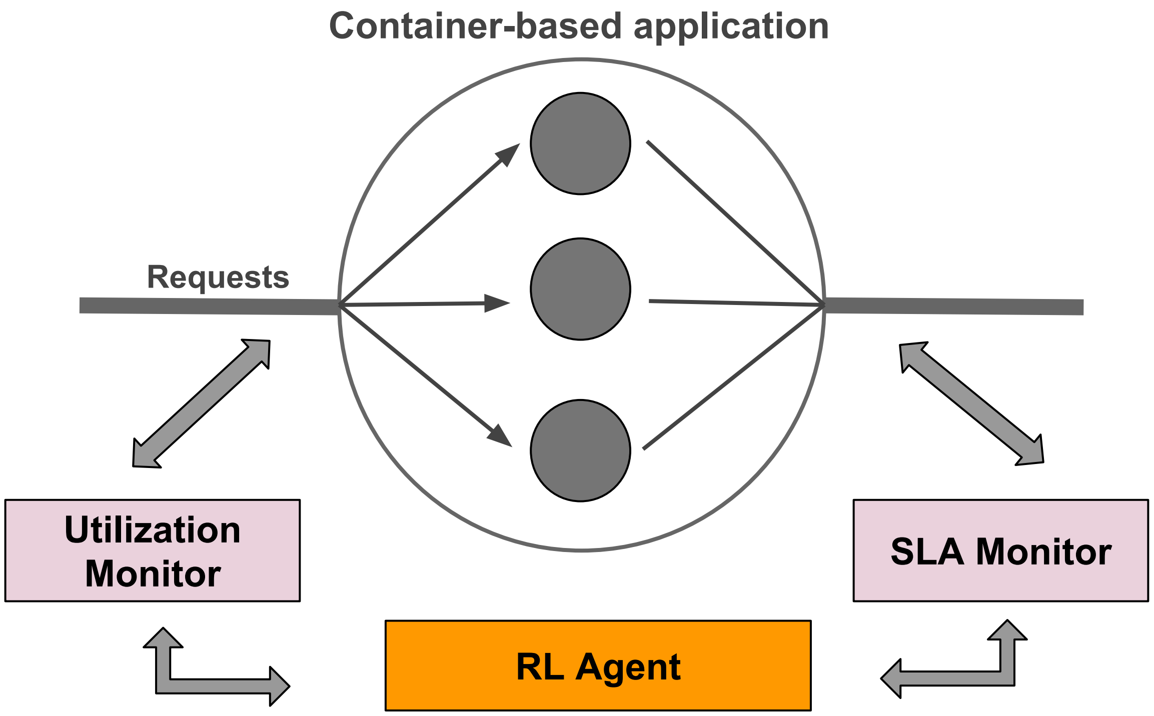
- **<u>Idea: to approximate unknown factors using experience</u>**

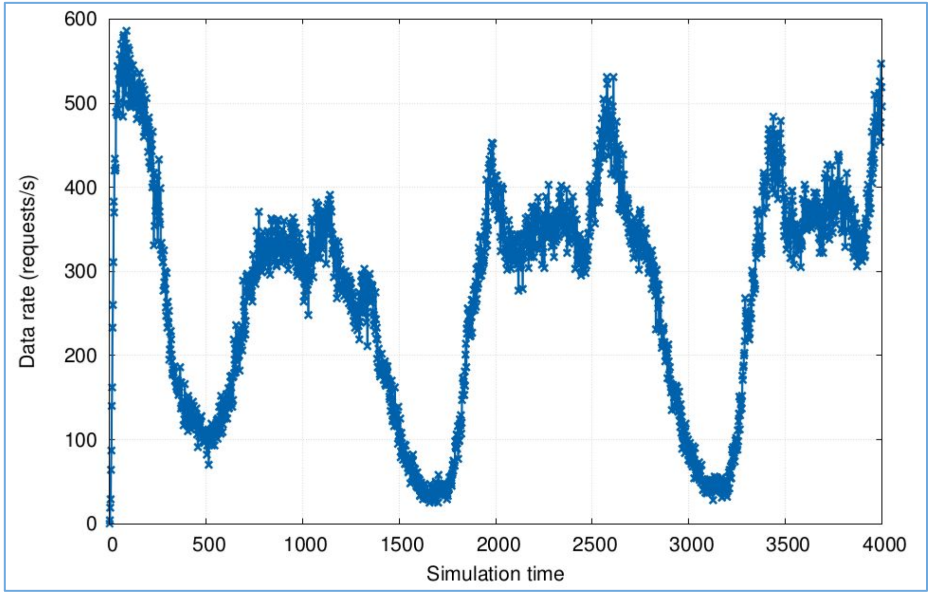
Evaluation

Container Deployment Simulator

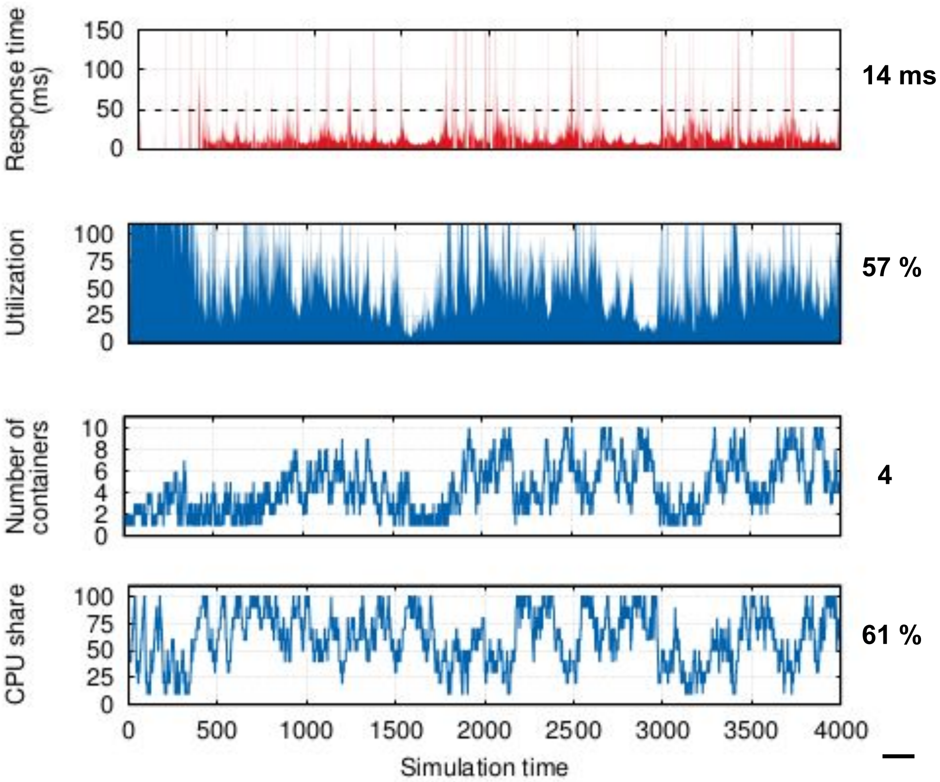


Experimental setting

$$c(s, a, s') = w_{\mathrm{rcf}} \cdot c_{\mathrm{rcf}}$$
$$+ \boxed{w_{\mathrm{perf}}} \cdot c_{\mathrm{perf}}$$
$$+ w_{\mathrm{res}} \cdot c_{\mathrm{res}}$$

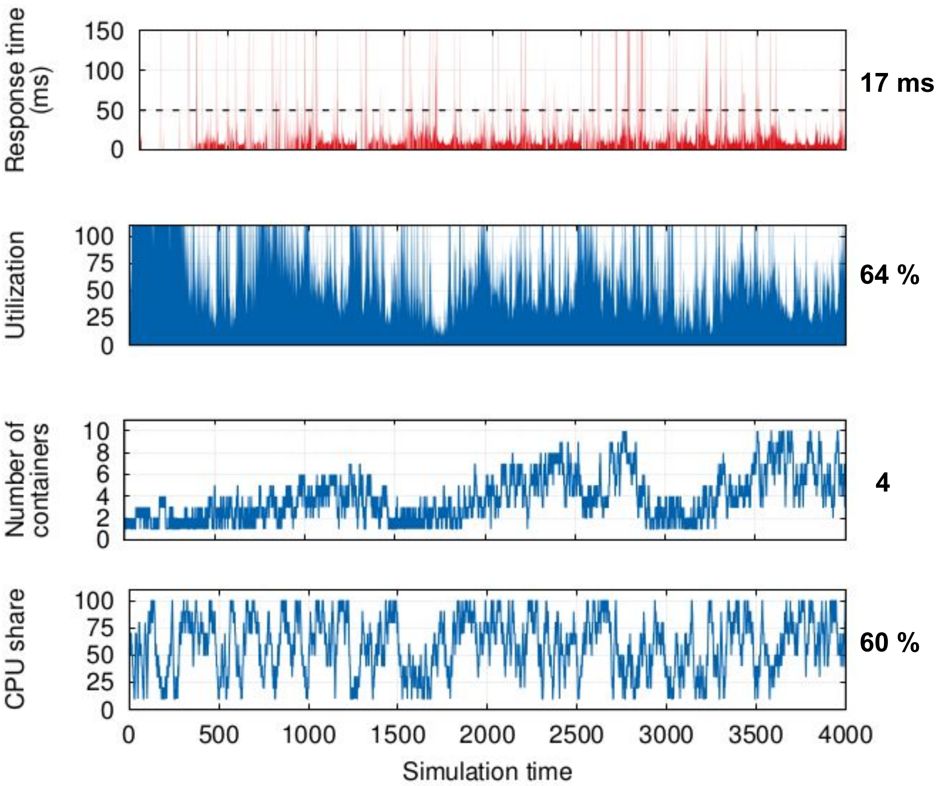


Q-learning
(5 actions)

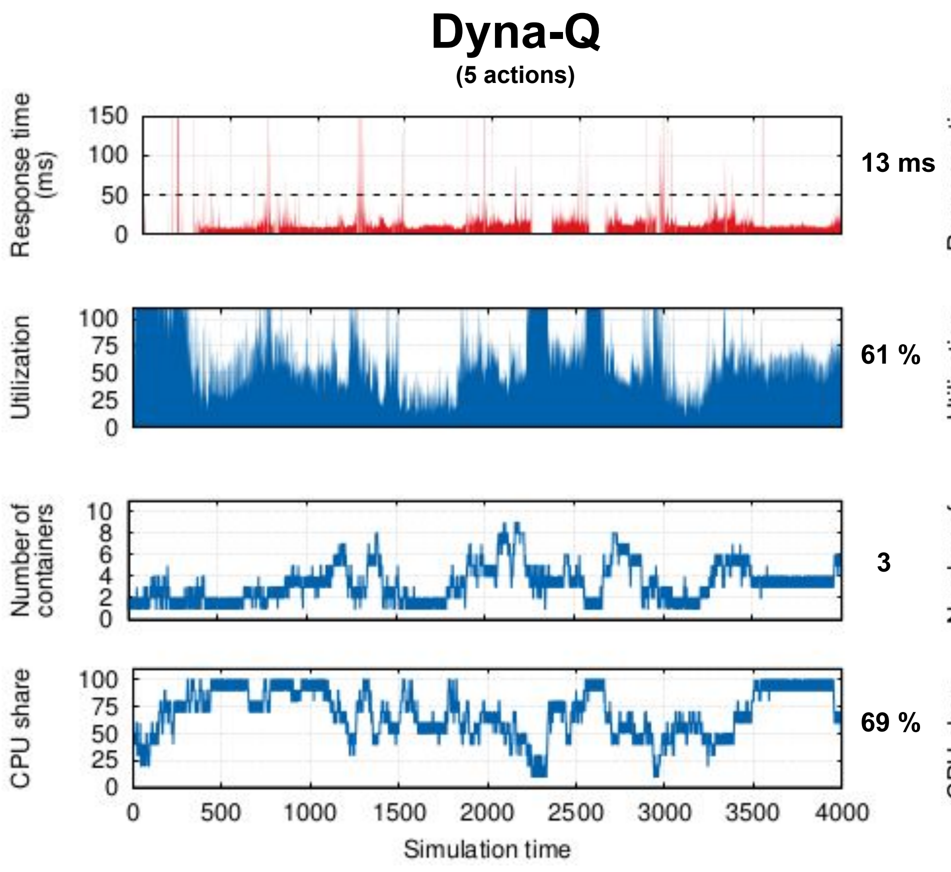


n. SLA violations: 18.52%

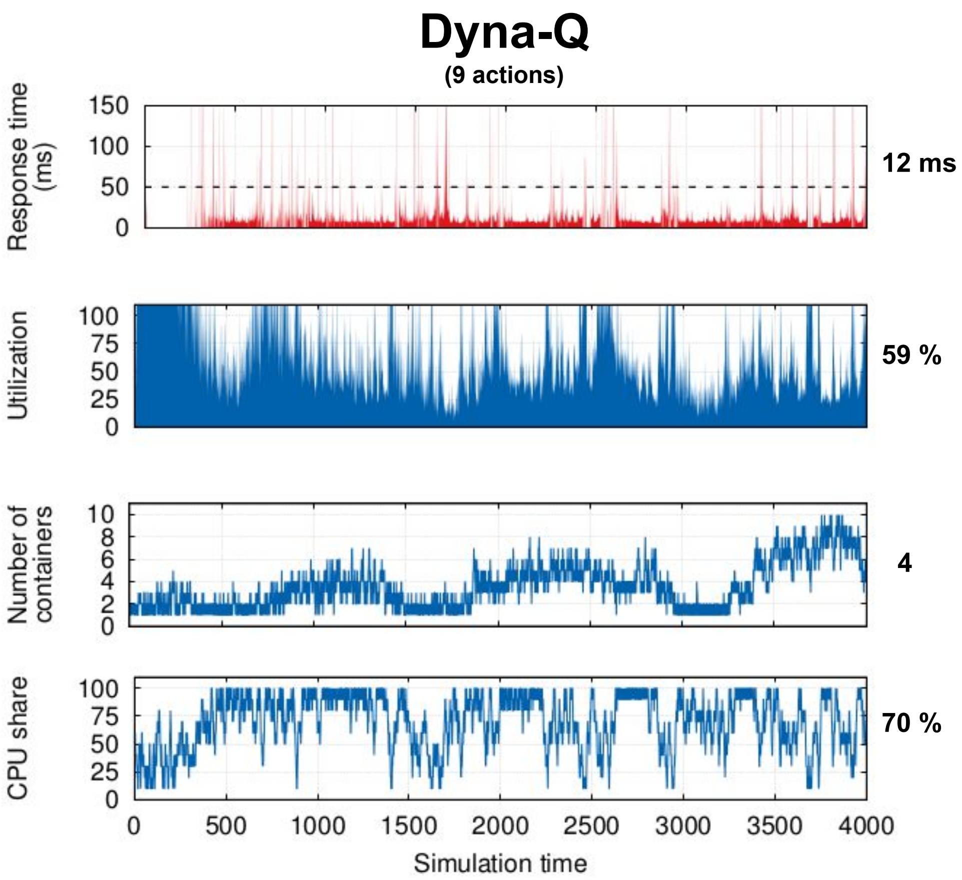
Q-learning
(9 actions)



n. SLA violations: 28.12%



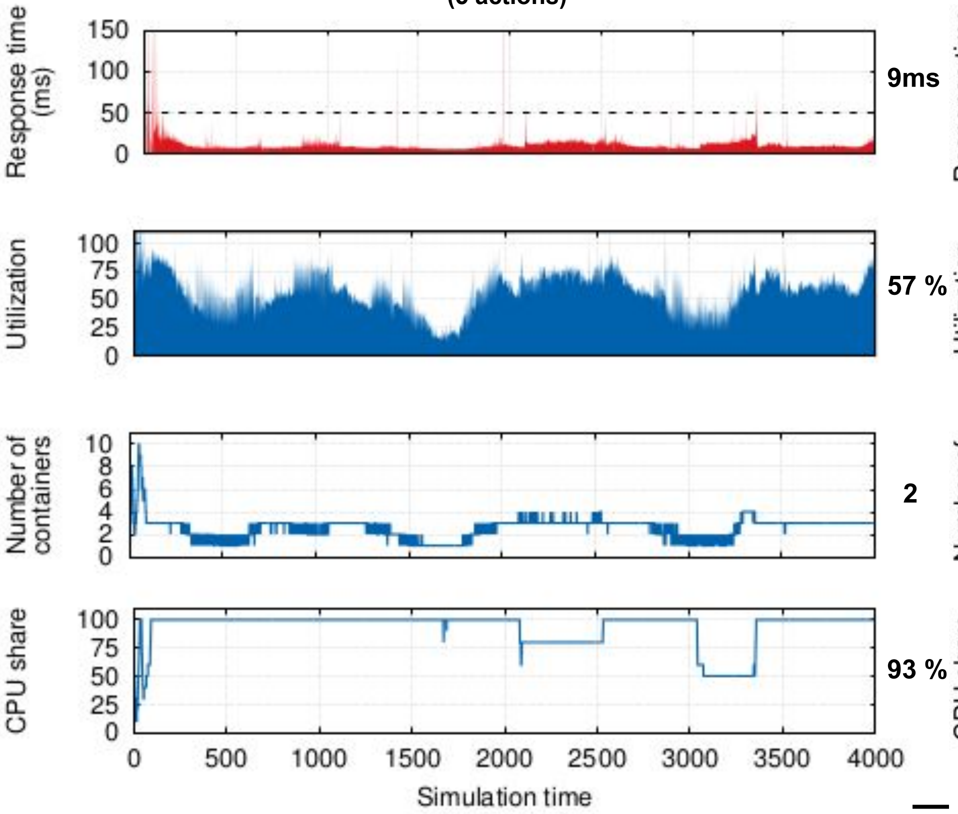
n. SLA violations: 17.92%



n. SLA violations: 21.54%

Model-based

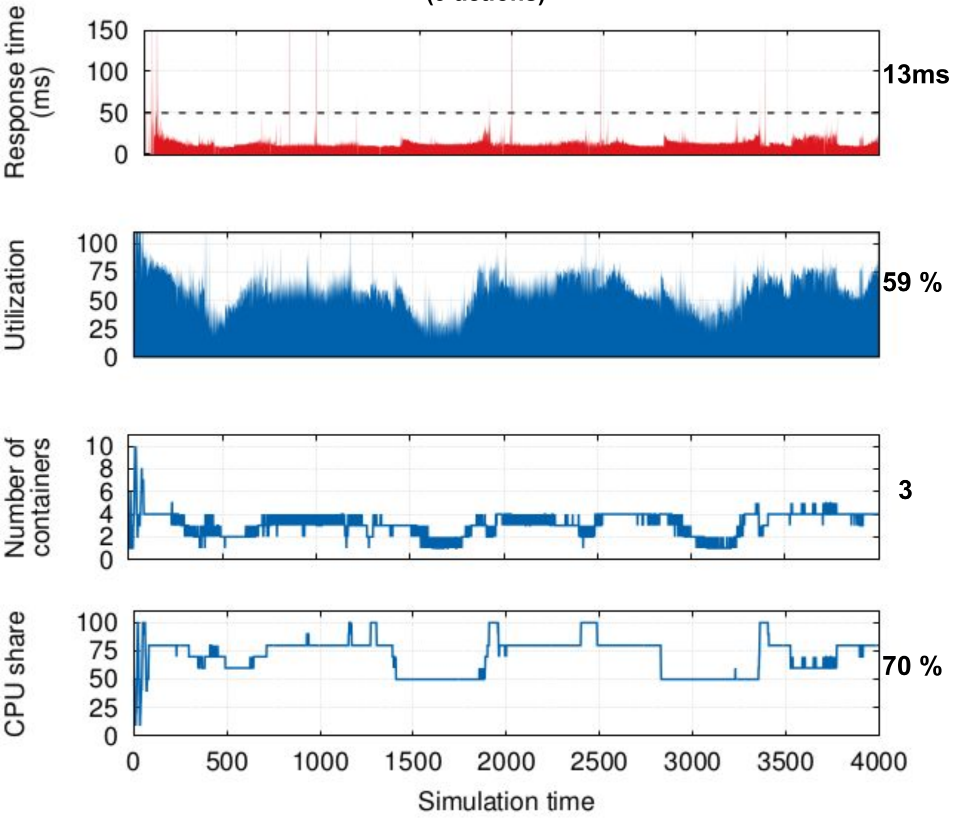
(5 actions)



n. SLA violations: 1.15%

Model-based

(9 actions)



n. SLA violations: 1.60%

Conclusion

- We designed RL-based solutions for the autonomic elasticity of containers
- We evaluated different techniques and system models
- We showed the benefits of model-based approaches
  - they reduce n. of SLA violations
  - they more quickly learn adaptation policies

Ongoing Work:

- To prototype the proposed solution (e.g., using Docker Swarm)
- To consider resource heterogeneity and their geo-distribution

Thank you!

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Simulation Configuration

- Application modeled as a M/D/*n* queue
  - *n*: number of containers
  - application rate $\mu = 200 \cdot c$ requests/s, where $c \in (0, 1]$ is the CPU share assigned to application;
- Target response time: 50 ms
- Max number of containers per-application: 10
- Discretization factors:
  - Utilization: 10%
  - CPU share: 10%
- Weights: w_rcf = 0.001, w_res = 0.019, w_perf = 0.98

Internet of Things

Empowering IoT Edge Computing

To fully attain the potential of edge computing for IoT, we need to address four concerns:

- hardware abstraction;
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→ **Software containers**

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Software containers

Elasticity

The possibility of cloud computing to provide resources on demand has encouraged the development of elastic applications.

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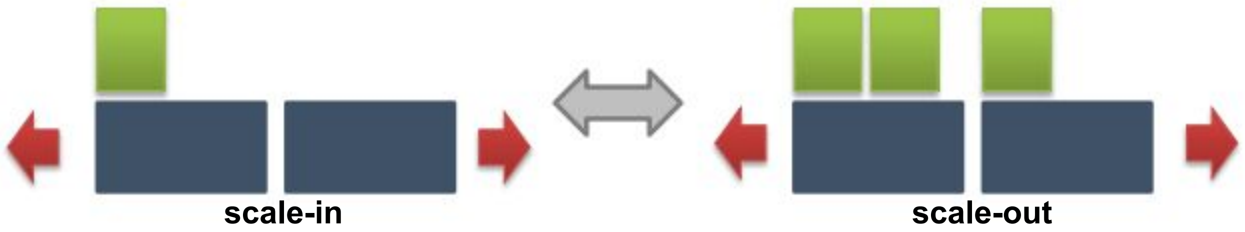
Horizontal Elasticity



Elasticity

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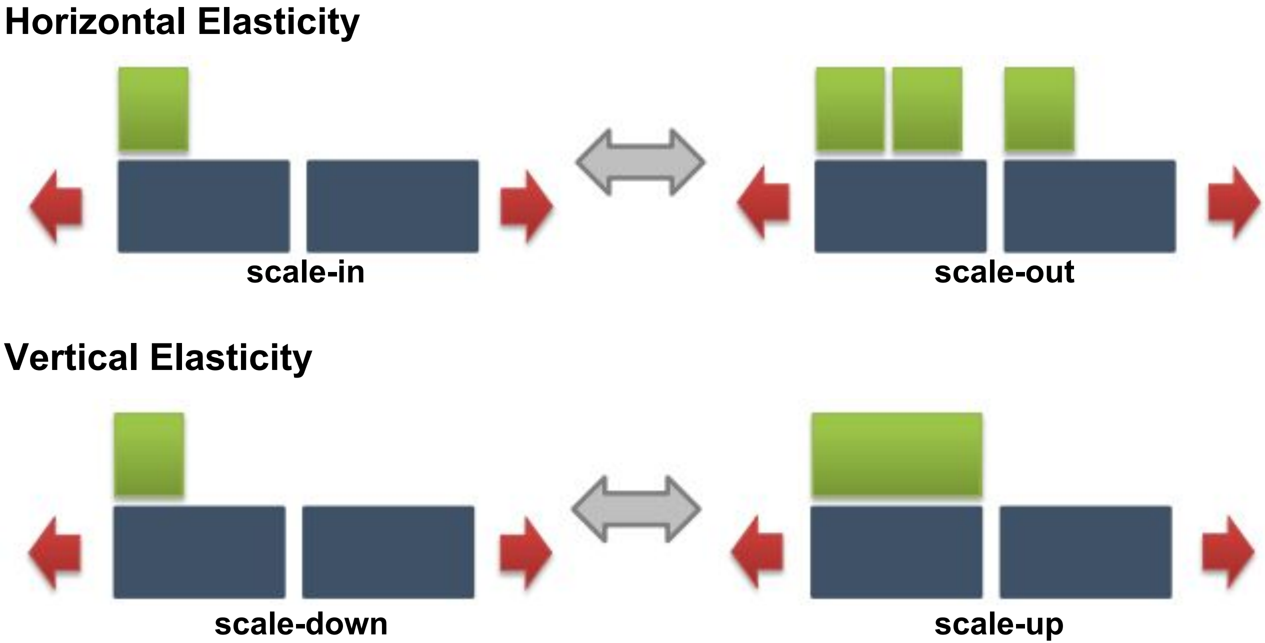
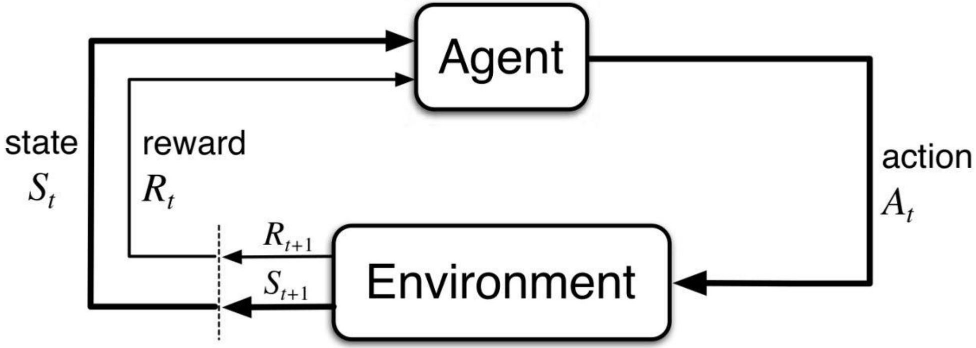


Reinforcement Learning

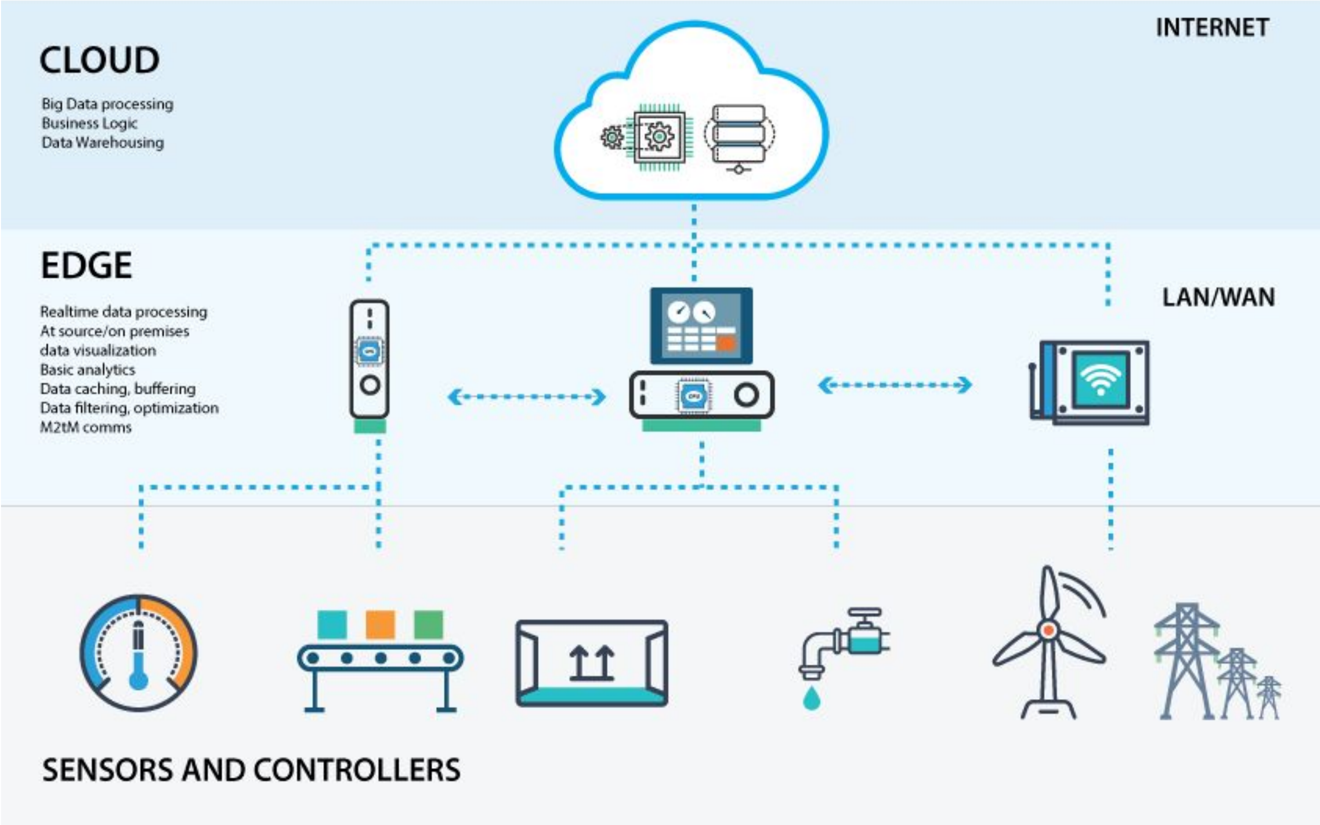
RL is a machine learning technique, where:

- the agent learns how to map situations to actions through the experience.

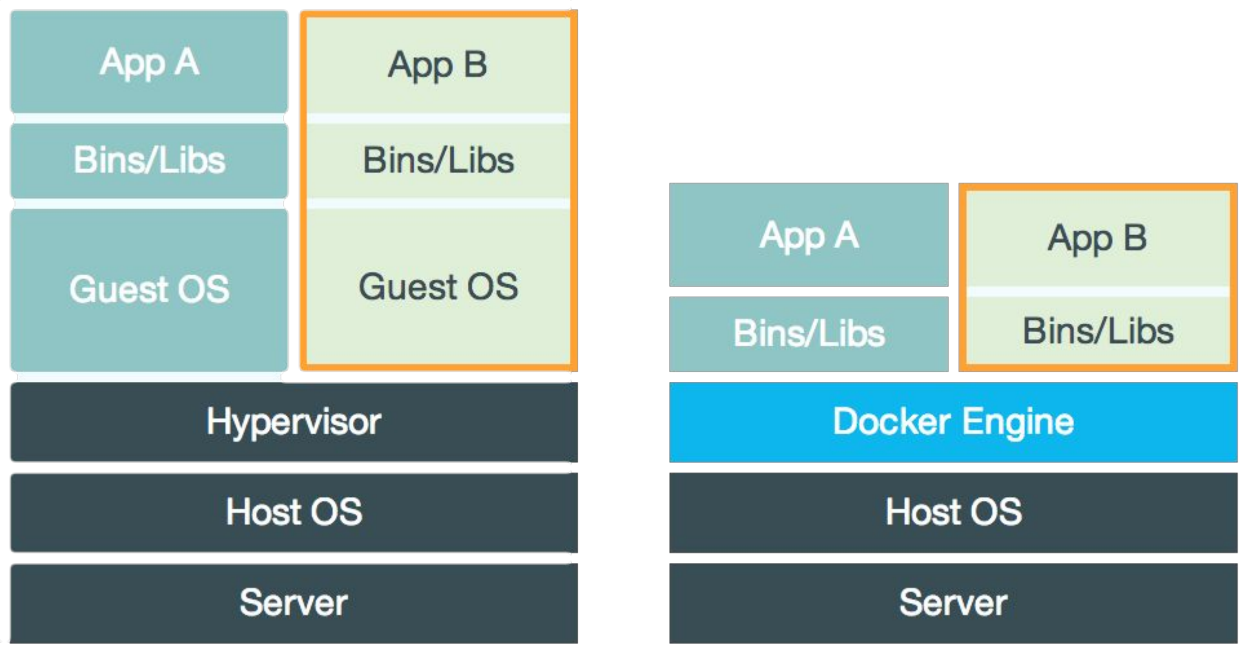


Sutton, R. S., and Barto, A. G. Reinforcement learning: An introduction. MIT Press, Cambridge, 1998.

Three-tier IoT Edge Computing Infrastructure



Virtualization techniques comparison



Virtual machines

Software containers

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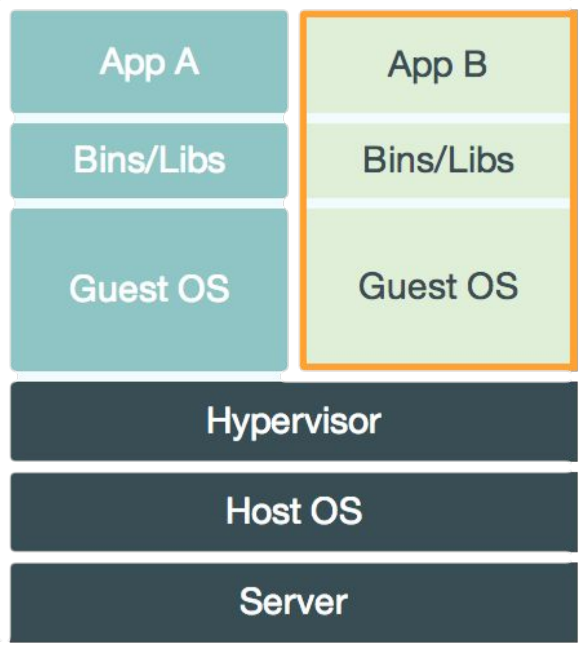

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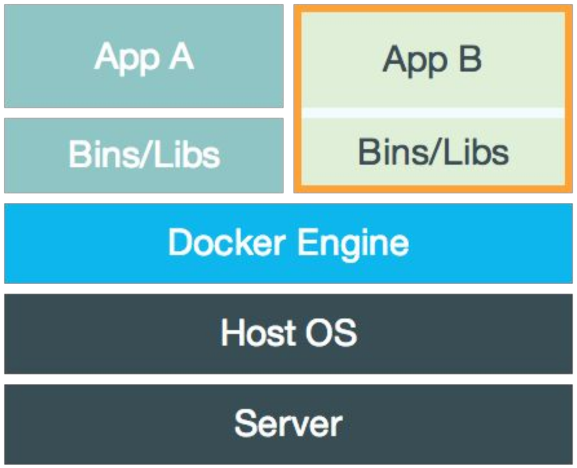


Software containers

Known and Unknown Cost

To estimate *c(s, a, s')*, it is divided into two terms: **known** and **unknown cost**.

$$c(s, a, s') = \underbrace{\boxed{w_{\text{rcf}} \cdot c_{\text{rcf}} + w_{\text{res}} \cdot c_{\text{res}}}}_{\text{known cost}} + \underbrace{\boxed{w_{\text{perf}} \cdot c_{\text{perf}}}}_{\text{unknown cost}}$$

To **update** the **unknown cost estimate**:

$$\hat{c}_u(s') \leftarrow (1 - \alpha)\hat{c}_u(s') + \alpha c_u$$

Estimated Transition Probability

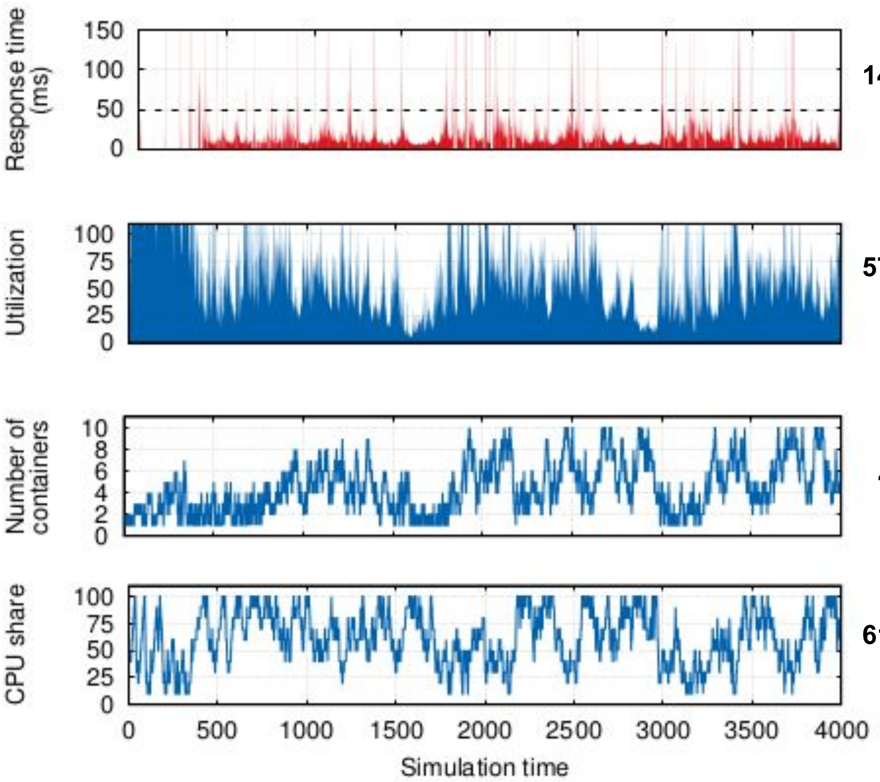
The **transition probability** is defined as

$$
\begin{aligned}
p(s'|s,a) &= P[s_{i+1} = (k', u', c')|s_i = (k, u, c), a_i = a] = \\
&= \begin{cases} P[u_{i+1} = u'|u_i = u] & k' = k + a_1 \wedge c' = c + a_2 \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
$$

Given $u = j\bar{u}$ and $u' = j'\bar{u}$ at time instant *i*, the **estimated transition probability** is

$$
\widehat{P_{j,j'}} = \frac{n_{i,jj'}}{\sum_{l=0}^{L} n_{i,jl}}
$$

Q-learning
(5 actions)



14 ms

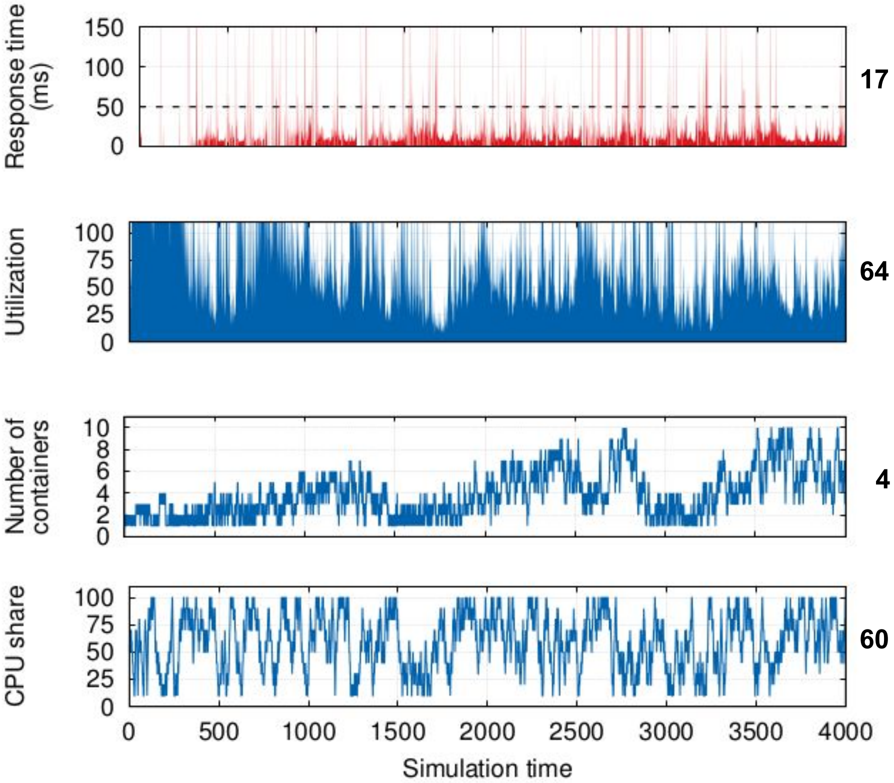
57 %

4

61 %

n. reconfigurations: 76.56%

Q-learning
(9 actions)



17 ms

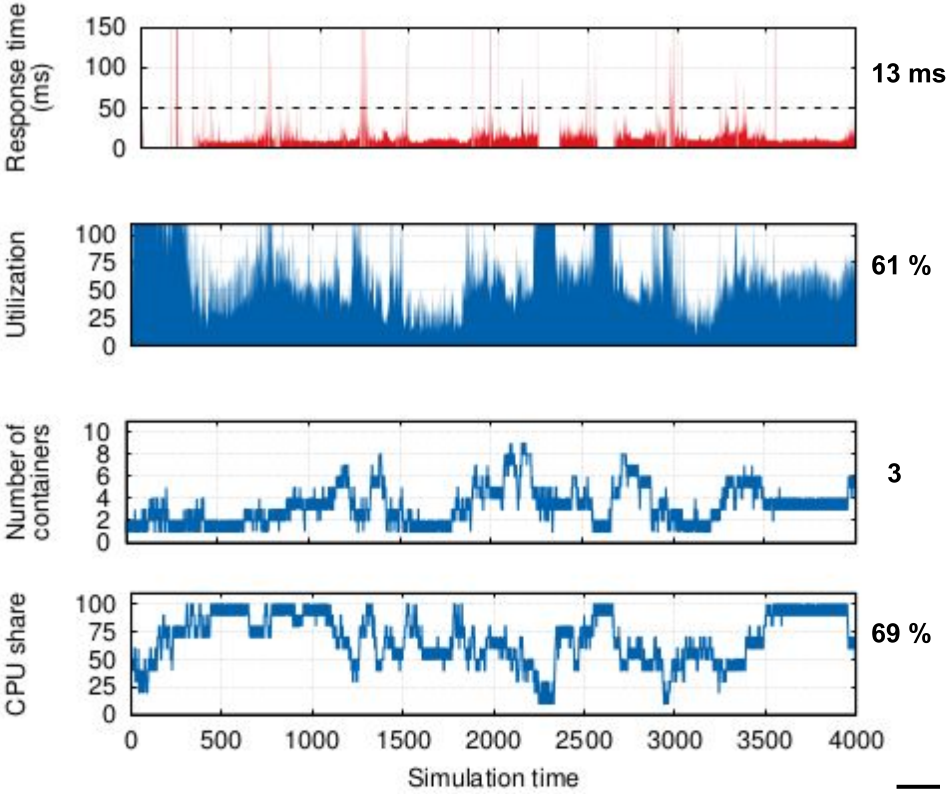
64 %

4

60 %

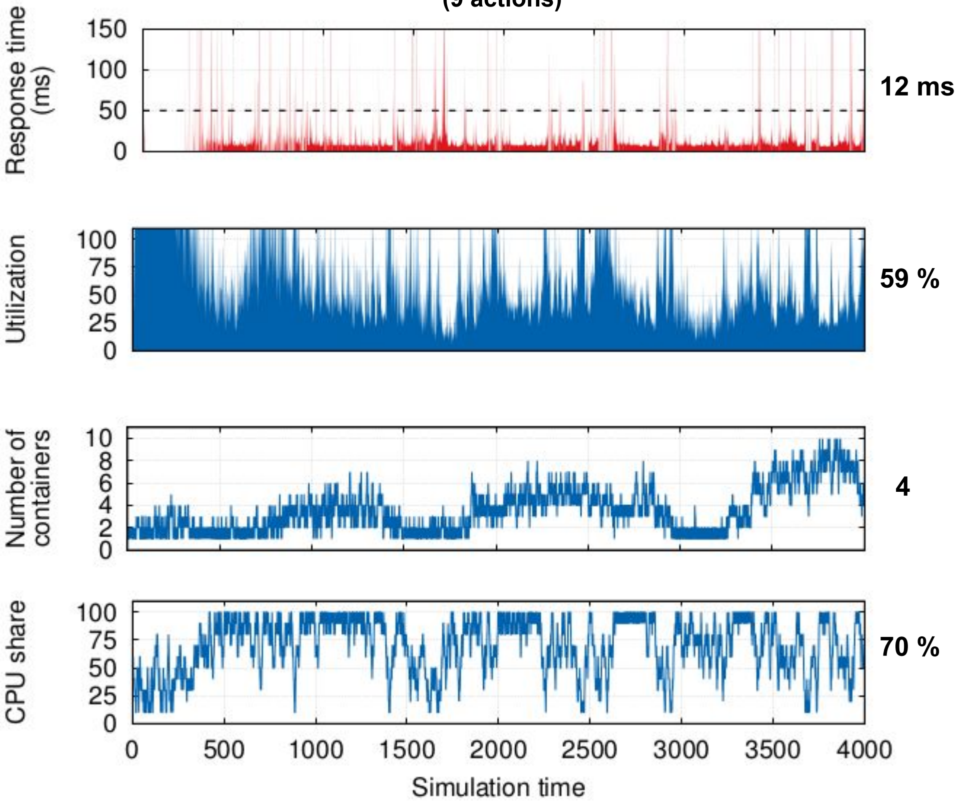
n. reconfigurations: 89.75%

Dyna-Q
(5 actions)



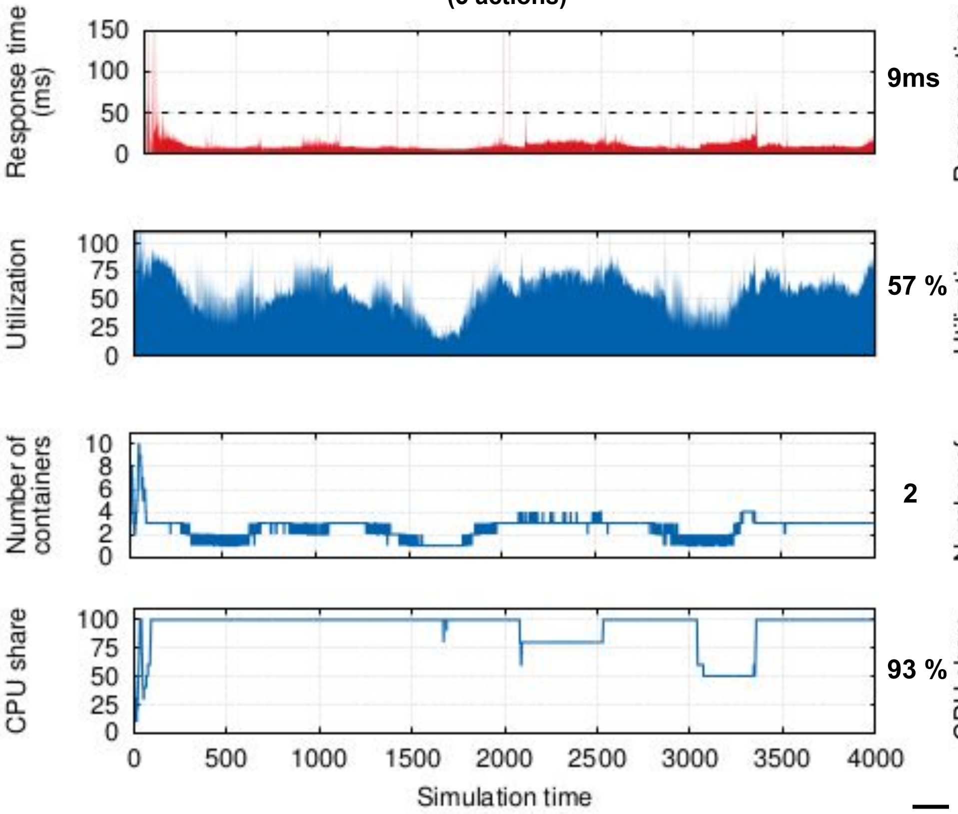
n. reconfigurations: 87.60%

Dyna-Q
(9 actions)



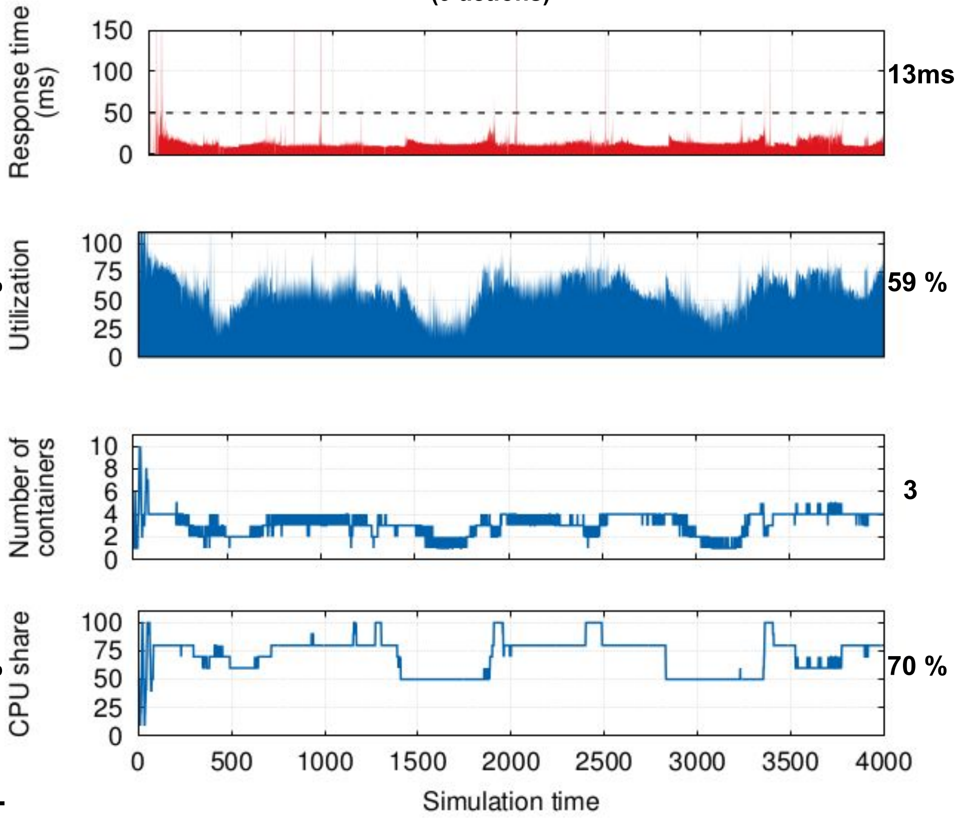
n. reconfigurations: 92.75%

Model-based
(5 actions)



n. reconfigurations: 34.09%

Model-based
(9 actions)



n. reconfigurations: 46.91%