Development and validation of an optimal self-adaptive SLA-oriented resource allocation algorithm for cloud computing

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The solution conceived by DELL-EMC

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Adaptive Control Strategies

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The OACS design

Testing

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Introduction

Current trends in Cloud Computing

Main idea: computational resources seen as an *on-demand* service

- Quality of Service ensured by Service Level Agreements (SLA), based on performance metrics;
- Need of a Resource Management System to deal with multiple applications sharing the same infrastructure.

Challenges:

- Power consumption in cloud data centers;
- Software development : widespread implementation of *micro services* - the use of **containers**;
- Diversity of workload profiles;
- Software systems usually not described by mathematical models.

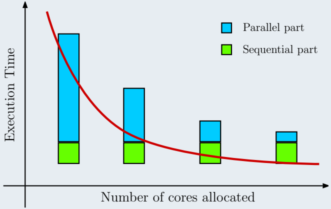
Introduction

The Resource Allocation Problem

Main goal

Determine the optimal amount of resources to satisfy a SLA defined as an upper bound in execution time.

Software Systems



Iterative Workload

- identical small jobs that run in succession;
- Examples: ML training and video encoding processes.

Control Theory

- model based technique;
- provides formal guarantees for an adequate performance.

The solution of this work

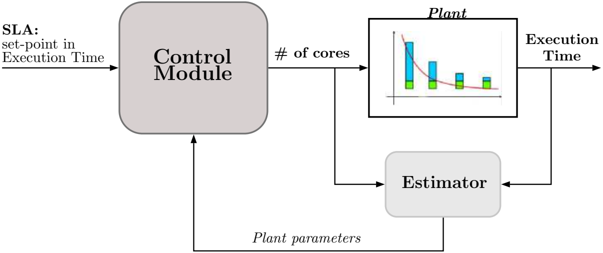
Develop and validate an algorithm applying **control techniques** to provide the **optimal** resource allocation in a **self-adaptive** approach, specifically for iterative workloads.

Introduction

The Resource Allocation Problem

The approach considered in this work

- Every application is seen as a plant to be controlled;

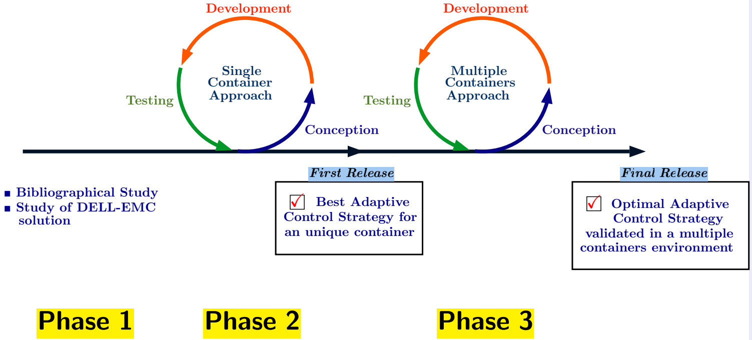


- **Multiple applications** seen as different plants (sub-systems) to be managed by a centralized control module.

Introduction
Organization of the work in this project

- Define a model for the workload characteristics
- Design Adaptive Control Strategies
- Study the performance of all strategies under different operating conditions

- Conceive a new Structural Architecture
- Design the global OACS
- Validate the deployment of multiple containers using the OACS under different scenarios



Related work

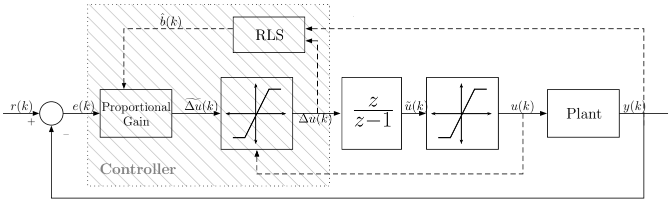
The self-adaptive concept: a parametric adaptation *(in most cases)*

Current solutions developed:

- In Research Community:
  - Model: gray-box, discrete non-linear time-invariant;
  - Parameters Identification: using an Initial Phase dedicated to it. Most of them using a Kalman Filter;
  - Controller Types: PID, MPC, LLC;
  - Presence of *change point detection mechanisms* to deal with some model inconsistencies.
- In Industry: **No self-adaptation implemented**

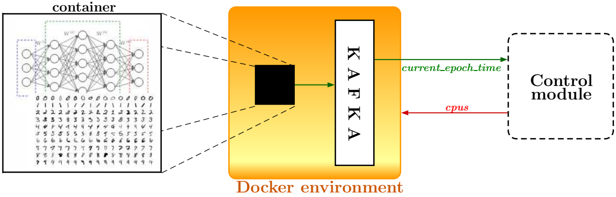
- Use of control techniques, but the client must specify details related to the workload;
- Client defines boundary values for each resource type;

The solution conceived by DELL-EMC
Control System Block Diagram



- Plant: relationship between **# of cores**$(u(t))$ and **Execution Time**$(y(t))$
- Model: $x(k+1) = x(k) + \beta\Delta u(k)$
  $y(k) = x(k)$
- Control input: $\Delta u(k)$
- Online estimation using **R**ecursive **L**east **S**quares
  - Regression model: $x(k+1) - x(k) = \hat{\beta}\Delta u(k)$
  - Estimated parameter is applied only after Identification Phase.
- Control law: $\Delta cpus(k+1) = \frac{1}{\hat{\beta}(k)} e(k)$

The solution conceived by DELL-EMC
System Structural Architecture and Performance Analysis



Testing Campaign
(Workload profile: ML training process - MNIST data-base)

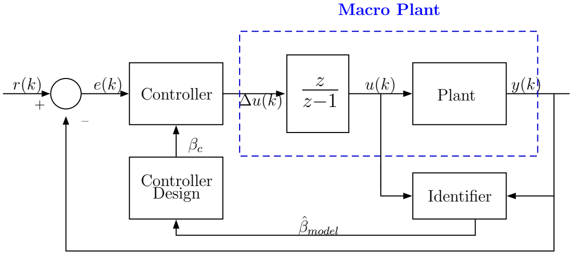
- SLA: constant set-point in all epochs.

Performance in steady state	**Set-point values**			
	12.5s	**25.0s**	**50.0s**	**100.s**
Set-point tracking error achieved?	YES	YES	NO	NO
Mean value [s]	12.42	25.06	51.39	106.41
Variance [s^2]	0.04	1.32	48.65	351.09
$\hat{\beta}$	constant	constant	variant	variant
RLS estimation error	converges to zero	converges to zero	variant	variant

ACS for a single container

Adaptive Control Strategies

Control System Block Diagram



- **Plant model:** 2 candidate functions
  - Hyperbolic function: $TTF(k) = \alpha + \beta \frac{1}{cpus(k)+\gamma}$
  - Exponential function: $TTF(k) = \alpha e^{\beta cpus(k)} + \gamma$, $\beta < 0$

  where $TTF(k)$ is the time execution.
- **Estimation:** linear parameterization; γ considered as a constant : γ_0
  - **Without** an initial Identification Phase;
  - Additional mechanism to better manage high estimation errors.
- **Controller Type:** Dead-beat

ACS for a single container

Adaptive Control Strategies

Workload characteristics as a hyperbolic function

Control Strategy 1 (using Taylor expansion)

- Dynamics: $TTF(k+1) = TTF(k) - \frac{\beta_c \Delta cpus}{[cpus(k) + \gamma_0]^2}$
- Dead-beat control law: $\Delta cpus = -\frac{[cpus(k) + \gamma_0]^2}{\hat{\beta}_c}(sp\_error)^{i}$
- Relationship between $\hat{\beta}_c$ and $\hat{\beta}$: $\hat{\beta}_c = \frac{[cpus(k) + \gamma_0]}{[\hat{cpus}(k+1) + \gamma_0]}\hat{\beta}$

Control Strategy 2 (using the exact hyperbolic function)

$$TTF(k) = \alpha + \frac{\beta}{cpus(k) + \gamma_0} \Rightarrow TTF(k+1) = \alpha + \frac{\beta}{(cpus(k) + \Delta cpus) + \gamma_0}$$

- Dynamics: $TTF(k+1) = TTF(k) - \beta \frac{\Delta cpus(k)}{(cpus(k) + \gamma_0)^2 + \Delta cpus(k)[cpus(k) + \gamma_0]}$
- Dead-beat control law: $\Delta cpus(k) = -\frac{(cpus(k) + \gamma_0)^2 (sp\_error)^{i}}{(cpus(k) + \gamma_0)(sp\_error)^{i} + \hat{\beta}}$

[i] $sp\_error = set\_point - TTF(k)$

ACS for a single container

Adaptive Control Strategies

Workload characteristics as an exponential function

Control Strategy 3 (using Taylor expansion)

- Dynamics: $TTF(k+1) = TTF(k) - \beta_c \alpha e^{-\beta cpus(k)} \Delta cpus$
- Dead-beat control law: $\Delta cpus = -\frac{1}{\hat{\beta}_c} \frac{set\_point - TTF(k)}{TTF(k) - \gamma_0}$
- Relationship between $\hat{\beta}_c$ and $\hat{\beta}$: $\beta_c = \frac{e^{\hat{\beta}(cpus(k) - \hat{cpus}(k+1))} - 1}{cpus(k) - \hat{cpus}(k+1)}$

Control Strategy 4 (using the exact exponential function)

$$ln[TTF(k) - \gamma_0] = ln(\alpha) - \beta cpus(k)$$
$$\ln[TTF(k+1) - \gamma_0] = ln(\alpha) - \beta cpus(k) - \beta \Delta cpus$$

- Dynamics: $ln[TTF(k+1) - \gamma_0] = ln[TTF(k) - \gamma_0] - \beta \Delta cpus$
- Dead-beat control law: $\Delta cpus = -\frac{1}{\hat{\beta}} ln \left[\frac{set\_point - \gamma_0}{TTF(k) - \gamma_0} \right]$

ACS for a single container
Testing — Performance Analysis

(Workload profile: ML training process - MNIST data-base)

Main goals:

- Analyze the importance of γ_0 for the control input evaluation;
- Verify how the system adapts itself to new contexts :
  - change in set-point values;
  - resource usage limitation.

Common aspects in all test case phases

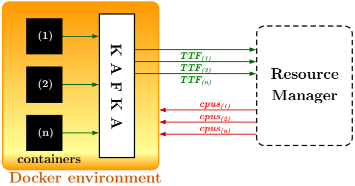
Candidate Function	**Hyperbolic**		**Exponential**	
Control Strategy	**ACS1**	**ACS2**	**ACS3**	**ACS4**
Set-point tracking	YES		NO	
Transient response	best	ok	ok	
$\hat{\beta}$ behavior [2]	constant		constant	
System response without considering γ_0	best	well-managed	ok	

Comparing all control strategies: ACS1 presents the best operation

Approach	Set-point values			
	12.5s	25.0s	50.0s	100.0s
SLA-oriented	**ACS 1**	**ACS 3**	**ACS 1**	**ACS 1**
resource usage-oriented	**ACS 1**	**ACS 1**	**ACS 1**	**ACS 1**

[2] in steady state

OACS for multiple containers
System Structural Architecture

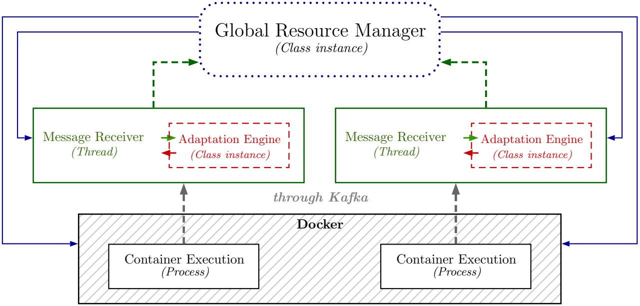


New functionalities required to handle multiple containers:

- Autonomous assignment of variables for container identification;
- Autonomous initial allocation of resources, based only on the current total amount available;
- Synchronization of events coming from different containers - use of Semaphores.

OACS for multiple containers

System Structural Architecture



OACS for multiple containers
The OACS design

Update on the Problem formulation

- SLA: an upper bound in execution time of a container;
- No *a priori* knowledge about the parameters of workload characteristics;

Constraint 1 *The amount of resources to be allocated to each container must be a positive value;*

Constraint 2 *The sum of all allocated resources in a given time cannot exceed the total number of resources provided by the infrastructure.*

Reformulating the dynamics of ACS 1

$$\begin{aligned} TTF(k+1) &= TTF(k) - \beta \tfrac{cpus(k)}{cpus(k+1)} \tfrac{\Delta cpus}{[cpus(k)]^2} \\ &= TTF(k) - \beta u(k) + \beta u(k+1) \quad , u(k) = \frac{1}{cpus(k)}. \end{aligned}$$

OACS for multiple containers

The OACS design - Control law design using MPC
The unconstrained control problem

Planta defined as a container

$$x(k+1) = x(k) - \beta u(k) + \beta u(k+1)$$
$$y(k) = x(k)$$

Control law design

MPC: control law considers a prediction horizon N_P

In a matrix form: $\mathbf{y} = \mathbf{f}x(k_i) - \beta \mathbf{f}u(k_i) + \beta \mathbf{I}_{N_P}\mathbf{u}$,

$$\begin{aligned}
\mathbf{y} &= [y(k_i+1|k_i) \quad y(k_i+2|k_i) \quad \dots \quad y(k_i+N_P|k_i)]^T, \\
\mathbf{f} &= [1 \quad 1 \quad \dots \quad 1]^T, \\
\mathbf{u} &= [u(k_i+1|k_i) \quad u(k_i+2|k_i) \quad \dots \quad u(k_i+N_P|k_i)]^T
\end{aligned}$$

Optimization

Cost function: $J = (\mathbf{r_s} - \mathbf{y})^T(\mathbf{r_s} - \mathbf{y}) + \mathbf{u}^T\bar{\mathbf{R}}\mathbf{u}$,
with $\bar{\mathbf{R}} = r_w \mathbf{I}_{N_P}$ and $\mathbf{r_s}^T = [1 \dots 1]r(k_i)$

$$\frac{\partial J}{\partial U} = 0 \implies \mathbf{u}^* = \beta(\beta^2 \mathbf{I}_{N_P} + \bar{\mathbf{R}})^{-1}(\mathbf{r_s} - \mathbf{f}x(k_i) + \beta \mathbf{f}u(k_i))$$

OACS for multiple containers

The OACS design - Control law design using MPC
The unconstrained control problem

Control law design - Implementation

Only the first predicted value is implemented:

$$u(k+1)^* = \underbrace{[1 \quad 0 \quad \dots \quad 0]}_{N_P}\mathbf{u}^* = \frac{\beta}{\beta^2 + r_w}(r_s - x(k_i) + \beta u(k_i))$$

The prediction horizon has **no** influence in the optimal control law.

Tuning parameter r_w:

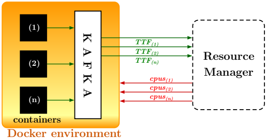
$$x(k+1) = x(k) - \beta u(k) + \beta \frac{\hat{\beta}}{\hat{\beta}^2 + r_w}(r_s - x(k_i) + \hat{\beta} u(k_i))$$

Two conditions: $\frac{\beta\hat{\beta}}{\hat{\beta}^2+r_w} = 1$ and $\frac{\beta\hat{\beta}^2}{\hat{\beta}^2+r_w} = \beta \implies r_w = 0$ and $\hat{\beta} = \beta$.

OACS for multiple containers

The OACS design - Control law design using MPC
The unconstrained control problem

- Every single container is considered as different SISO plant without coupling variables



The optimal control solution - the unconstrained case

For a single container: $u(k+1)^* = \frac{1}{\hat{\beta}}(r_s - x(k_i)) + u(k_i)$

Extending to multiple containers:

$$\mathbf{u}(k_i+1)^* = (\mathbf{I}_j \mathbf{b}(k_i))^{-1}(\mathbf{r_s} - \mathbf{x}(k_i)) + \mathbf{u}(k_i) \quad (1)$$

where

$$\begin{aligned} \mathbf{b}(k_i) =& [\hat{\beta}_1(k_i) \quad \hat{\beta}_2(k_i) \quad \dots \quad \hat{\beta}_j(k_i)]^T, \\ \mathbf{r_s} =& [r_{s1} \quad r_{s2} \quad \dots \quad r_{sj}]^T, \\ \mathbf{x}(k_i) =& [x_1(k_i) \quad x_2(k_i) \quad \dots \quad x_j(k_i)]^T, \\ \mathbf{u}(k_i) =& [u_1(k_i) \quad u_2(k_i) \quad \dots \quad u_j(k_i)]^T, \end{aligned} \quad (2)$$

OACS for multiple containers

The OACS design - Control law design using MPC
The constrained control problem

The optimal control solution - the constrained case

$$
\begin{aligned}
\min_{cpus_n} \quad & \sum_{n=0}^{j} (r_{sn} - x_n(k_i+1))^2 \\
\text{s.t.} \quad & x_n(k+1) = x_n(k) - \hat{\beta}_n u_n(k) + \hat{\beta}_n u_n(k+1) \\
& u_n(k_i) = \frac{1}{cpus_n} \\
& cpus_n \geq min\_cpus \\
& \sum_{n=0}^{j} cpus_n < total\_cpus
\end{aligned} \tag{3}
$$

OACS for multiple containers

The OACS design - Control law design using MPC
The constrained control problem

The optimal control solution - the constrained case

$$
\begin{aligned}
\min_{cpus_n} \quad & \sum_{n=0}^{j} \hat{\beta}_n^2 u_n^2(k_i+1) - 2\hat{\beta}_n u_n(k_i+1)(r_{sn} - x_n(k) + \hat{\beta}_n u_n(k)) \\
\text{s.t.} \quad & u_n(k_i) = \frac{1}{cpus_n} \\
& cpus_n \geq min\_cpus \\
& \sum_{n=0}^{j} cpus_n < total\_cpus
\end{aligned}
\tag{3}
$$

OACS for multiple containers

The OACS design - The global solution

Algorithm 1: The optimal adaptive control input evaluation algorithm

Input : The **container_id** whose resource allocation is about to be updated;
The total amount of resources available **total_cpus**;
The data $(cpus(k-1), ttf(k-1))$ from **container_id** ;
For the other running containers, their current resource allocation **cpus(k)** ;
For each running container: the estimated value $\hat{\beta}$ and the set-point value *sp*.
Output: The amount of resources **cpus(k+1)** to be allocated to **container_id**

```
Estimate TTF(k) for the running containers, using TTF(k) = α̂ + β̂/cpus(k)
Form vectors b(k_i) , r_s, x(k_i) and u(k_i) from Equation (2)
Perform unconstrained optimal control law (Equation (1))
if u(k_i + 1)* < 0 then
    Perform additional mechanism
if ∑ 1/u(k_i + 1)* > total_cpus then
    Perform constrained optimization given by (3)
cpus(k+1) ← 1/u(k_i + 1)*
```

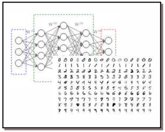
Implementing the global optimal solution

- Only a request for resource allocation is treated each time;
- Only part of the solution due to the container which requested the resource allocation is implemented.

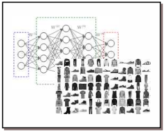
OACS for multiple containers

Testing Campaigns

- Workload profiles:



ML Training Process
MNIST data-base



ML Training Process
Fashion-MNIST data-base

Video encoding
Youtube video

OACS validation for the deployment of multiple containers

- Verify the management of all SLAs, including the introduction of new contexts at run-time:
  - The variation of the total amount of resources available;
  - The change in set-point values.
- Includes a monitoring of the CPU Clock Speed.

OACS for multiple containers

Tests — Real-time operation

Varying set-point with changes in environment

OACS for multiple containers
Testing - Performance Analysis

- **Changes in set-point values**:
  - Solution without important overshoots / undershoots;
  - When not all SLAs can be satisfied, the optimal solution minimizes the set-point tracking error.
- **Changes in the total available amount of cores**:
  - The first container to face this constraint is the most penalized in its performance;
  - The other containers reach quickly their new operating points.
- **Important events:**
  - Introduction of new containers / Ending of a container execution;
  - Change of the level of resource availability / parallel capacity;
  - Presence of oscillations in the CPU Clock Speed.

Change in the workload characteristic - change in the operating point

Adaptation mechanisms were vital to handle these unexpected events.

Conclusion and Perspectives

Conclusion

- With a **new model defining an iterative workload**, the OACS provides a solution that optimizes SLAs, respecting the available resources in a computational infrastructure.
- The resource allocation evaluation implemented in the OACS **only** uses data obtained at run-time.
- The use of **control techniques** associated to **decision-making mechanisms** guarantee the **self-adaptive** behavior of the system.

Perspectives

- Scale up the OACS to a larger number of applications;
- Develop a new multivariable control strategy at the level of each application;
- The extension of this work to other types of workloads.

Thank you!
Questions?