

Playing with power at runtime

Slightly slowed applications, major energy savings

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Journées calcul et données 2022

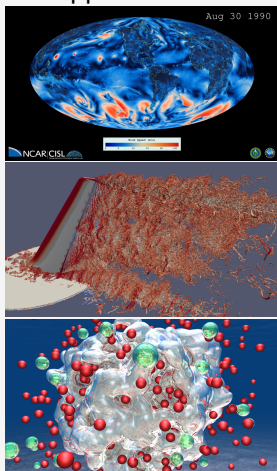
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High-Performance Computing

Applications ...



... running on Platforms



@ANL

Energy-aware HPC



@CBS

Performance/Energy Trade-off

Dynamic Management of HPC Systems

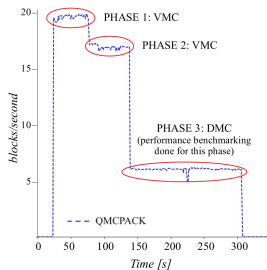
Highly variable systems ...

Offline

- HW spec.
- Aging

At runtime

- Phases
- Failures
- Temperature



(Ramesh et al. 2019)

... require dynamic management

How Scheduling, Autonomic computing, Machine Learning, Feedback **Control Theory** (Hellerstein et al. 2004)

Why Stability, performance guarantees, explainability

1 Introduction

- HPC and energy efficiency
- Dynamic Management using Control

2 Approach and Methodology

- Autonomic Computing Approach
- Control Theory: Principle & Methodology

3 Dynamic Power Regulation using Control Theory

- System Architecture
- Control Formulation

4 Experimental Evaluation

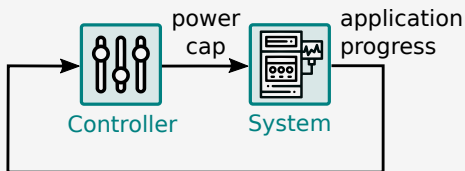
- Measure of the Model Accuracy
- Evaluation of the Controlled System

5 Perspectives and Conclusion

Autonomic Computing Approach

The Autonomic Computing approach... (Kephart et al. 2003)

- Periodically monitor application progress
- Choose at runtime a suitable power cap for processors



... using Control Theory

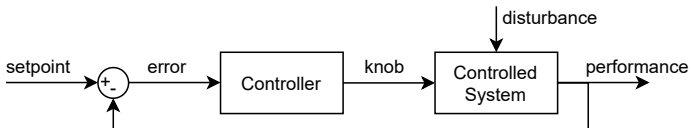
How Low-intrusive supervision

Why Stability, accuracy, transient performance, explainability
(Hellerstein et al. 2004)

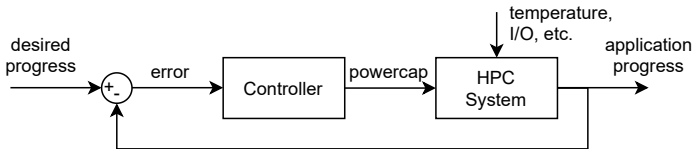
Principle of Control Theory

Feedback loops

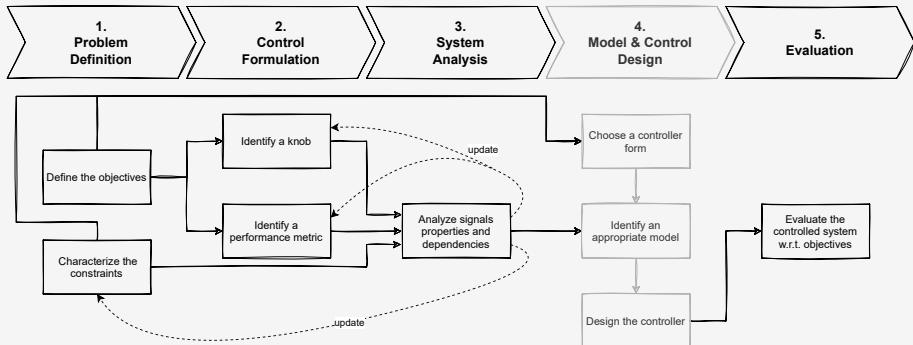
Measure **performance** and react according to the **error** w.r.t. the desired **setpoint** by leveraging system's **knob**.



Power control in HPC



Control Theory Methodology



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Dynamic Power Management

Global Objectives

- Sustain **execution time**
- Minimize **energy** usage

The Runtime Perspective

- Sustain application **progress**
- Minimize **power** usage

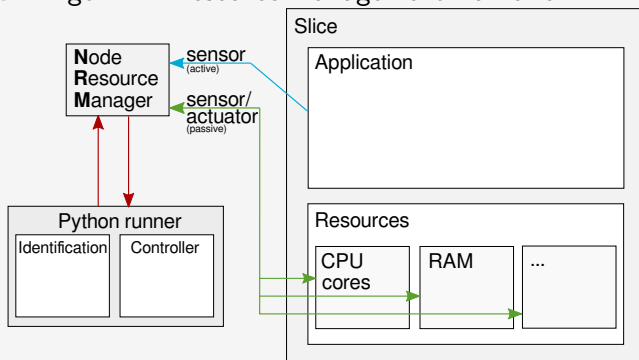
Actuator and Sensor

Power regulation DVFS (Imes et al. 2015; Imes et al. 2019);
DDCM (Bhalachandra et al. 2015);
RAPL (David et al. 2010; Rotem et al. 2012)

App. behavior Measuring progress with heartbeats (Ramesh et al. 2019)

Software Architecture

Software Stack Argo NRM resource management framework



Platform 3 clusters from Grid5000 with various nb. of sockets

Benchmark STREAM (McCalpin 1995)

Signals

Power actuator

RAPL's **power** limitation (David et al. 2010; Rotem et al. 2012)

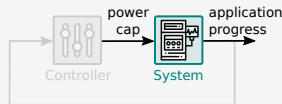
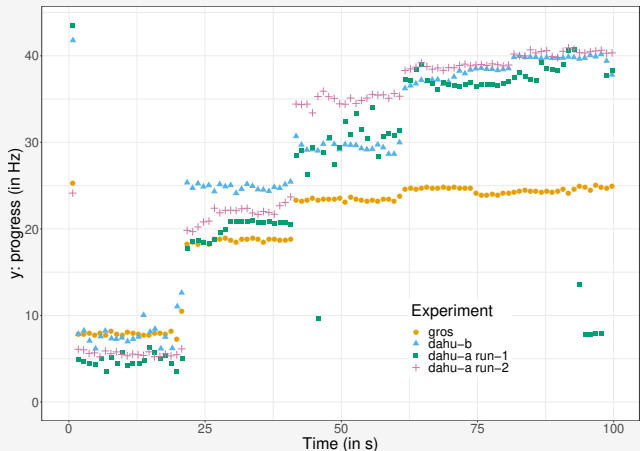
$$\text{pcap}(t_i)$$

Performance sensor

Application's **progress** (Ramesh et al. 2019)

$$\text{progress}(t_i) = \underset{\forall k, t_k \in [t_{i-1}, t_i[}{\text{median}} \left(\frac{1}{t_k - t_{k-1}} \right)$$

Uncontrolled System Analysis (Identification)

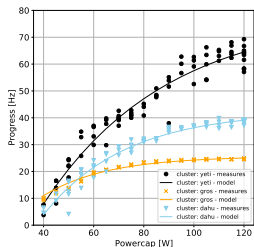


Many Sources of Variations

- Cluster
- Node
- Run
- Exogenous factors (temp., I/O)

Modeling

Static Characteristic (time averaged behavior)



$$\text{progress} = K_L \left(1 - e^{-\alpha(a \cdot \text{pcap} + b - \beta)} \right)$$

a, b: characterizing RAPL actuator

K_L , α , β : cluster- and application-specific

Dynamic perspective

$$\text{progress}_L(t_{i+1}) = \frac{K_L(t_{i+1} - t_i)}{t_{i+1} - t_i + \tau} \cdot \text{pcap}_L(t_i) + \frac{\tau}{t_{i+1} - t_i + \tau} \cdot \text{progress}_L(t_i)$$

Shape set by control theory, parameters optimized offline

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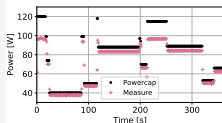
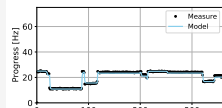
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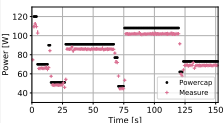
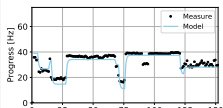
Experimental Evaluation

Measure of the Model Accuracy

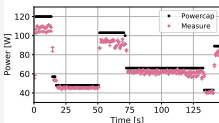
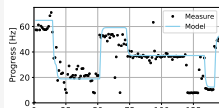
Not a prediction model but used to tune the controller



gros



dahu



yeti

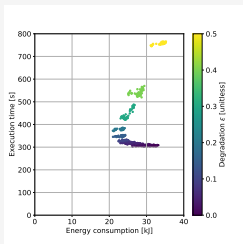
Observations

- Good accuracy.
- The model performs better on clusters with few sockets.

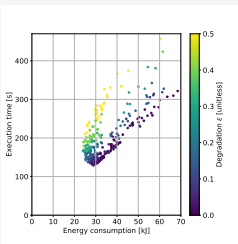
Experimental Evaluation

Post-mortem analysis

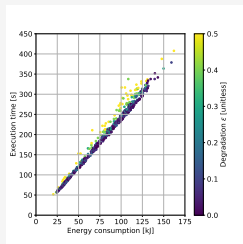
12 degradation levels, min. 30 repetitions each



gros



dahu



yeti

Pareto Front

gros, dahu Family of trade-off from 0% to 15% degradation level
 gros with $\epsilon = 0.1$: -22% energy, +7% execution time

yeti no front, no negative impact of the controller

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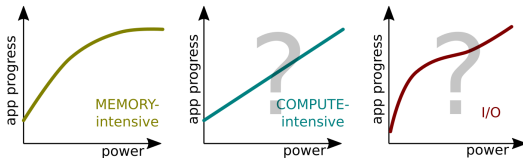
Perspectives

Applications' phases



Adaptation steps

1 Phases characterization



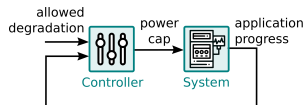
2 Online phase detection (?)

3 Dedicated control: robust, adaptive or hybrid

Conclusion

Objective Reducing energy consumption while sustaining performance

Approach Dynamic power regulation using Control Theory



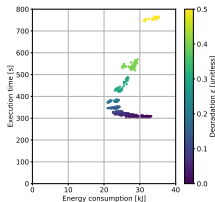
Contributions

- Control theory × HPC systems

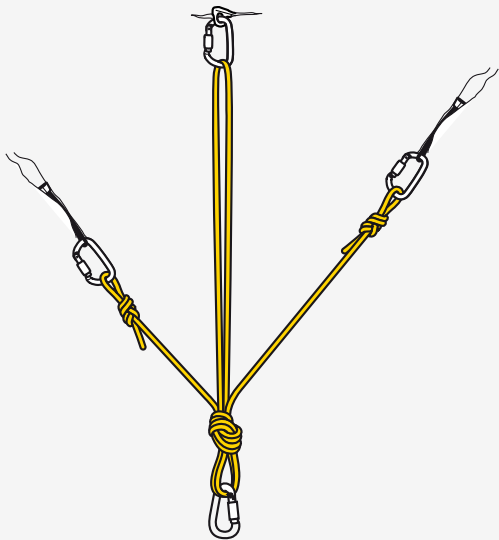


- Experimental validation on several clusters

<https://doi.org/10.6084/m9.figshare.14754468>



Open **post-doc/engineer** positions @CTRL-A!



Backup slides

Related Works

On power regulation in HPC

Different objective or static schema

(Eastep et al. 2017) application-oblivious monitoring

On using control theory for power regulation

Applications web servers (Abdelzaher et al. 2008), cloud (Zhou et al. 2016), real-time systems (Imes et al. 2015)

Metrics RAPL (Imes et al. 2019; Lo et al. 2014)
Progress metric (Santriaji et al. 2016)

Model and Controller Parameters

Description	Notation	Unit	gros	dahu	yeti
RAPL slope	a	[1]	0.83	0.94	0.89
RAPL offset	b	[W]	7.07	0.17	2.91
	α	[1/W]	0.047	0.032	0.023
power offset	β	[W]	28.5	34.8	33.7
linear gain	K_L	[Hz]	25.6	42.4	78.5
time constant	τ	[s]	1/3	1/3	1/3
	τ_{obj}	[s]	10	10	10
lower power limit	$pcap_{min}$	[W]	40	40	40
higher power limit	$pcap_{max}$	[W]	120	120	120

PI Controller Parameters Computation

K_P and K_I are based both on the model parameters K_L and τ and on a tunable parameter τ_{obj} (Åström et al. 1995):

$$K_P = \tau / (K_L \cdot \tau_{obj})$$

$$K_I = 1 / (K_L \cdot \tau_{obj})$$

with τ_{obj} defining the desired dynamical behavior of the controlled system.

The controller is chosen to be nonaggressive:

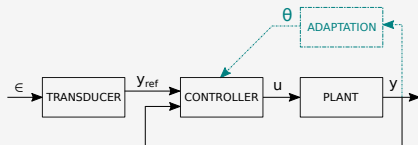
$$\tau_{obj} = 10 \text{ s} > 10\tau$$

Model Reference Adaptive Control

Model $y(k+1) = b_0u(k) + a_0y(k)$

Parameter vector $\theta = [s_0]$

Regression vector $\phi(k) = [y(k)]$



Control Law (Akhtar et al. 2005)

$$u(k) = -\frac{1}{b_0} \left[\phi^T(k) \hat{\theta}(k) - b_m y_{\text{ref}} \right]$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{1}{\phi^T(k-1)\phi(k-1)} \left[a_m y(k-1) - b_0 u(k-1) - \phi^T(k-1) \hat{\theta}(k-1) \right] \phi(k-1)$$

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