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Integrating Adaptive Components

by Jin Heo, Dan Henriksson, Xue Liu, Tarek Abdelzaher (2007) [1] [2]

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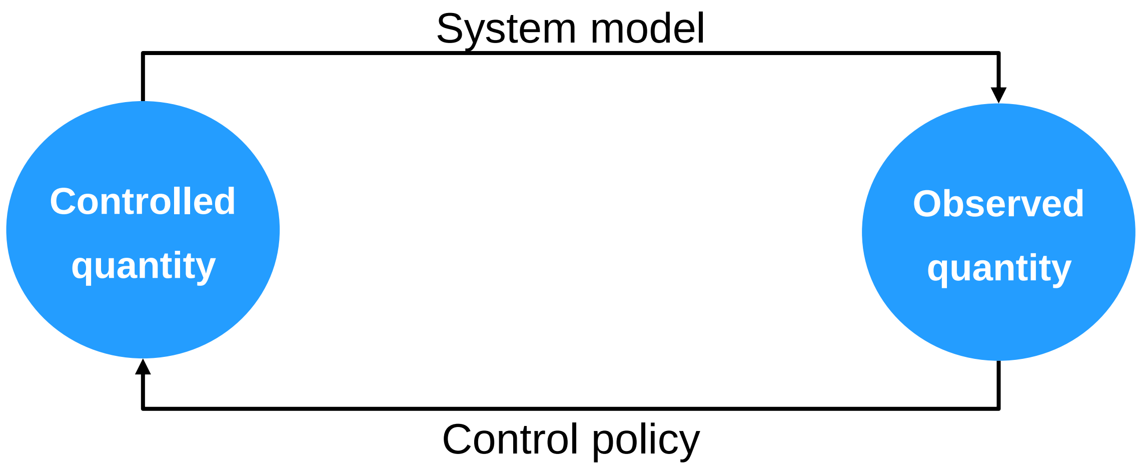
Problem

- Timing-sensitive and performance-sensitive systems (for example, data centers) are very complex
  - Manual tuning is imprecise, costly, and time-consuming
  - Hence: automation
- Automation calls for adaptive capabilities
  - Hence: adaptive components
  - Self-managing, self-calibrating, self-healing, self-tuning SW blocks
- Composition of locally stable adaptive components can lead to a globally unstable system

How to identify potential incompatibilities?

Adaptive components – Feedback loops

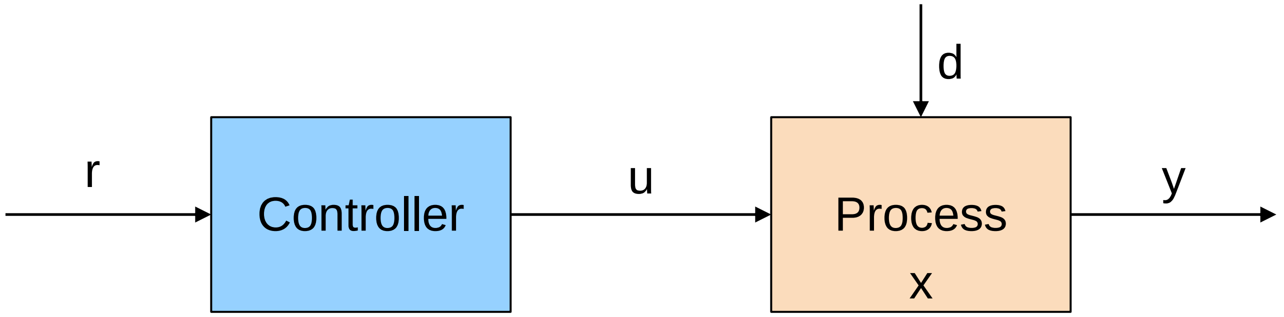


FEEDBACK CONTROL

Stability – Some insights

r: reference value
d: disturbance(s)
u: control variable(s)
x: state variable(s)
y: output variable(s)

Open-loop vs. closed loop control



Open-loop control:

- without feedback
- the effects of known disturbances are compensated (unknowns not)
- in case of a stable process always stable

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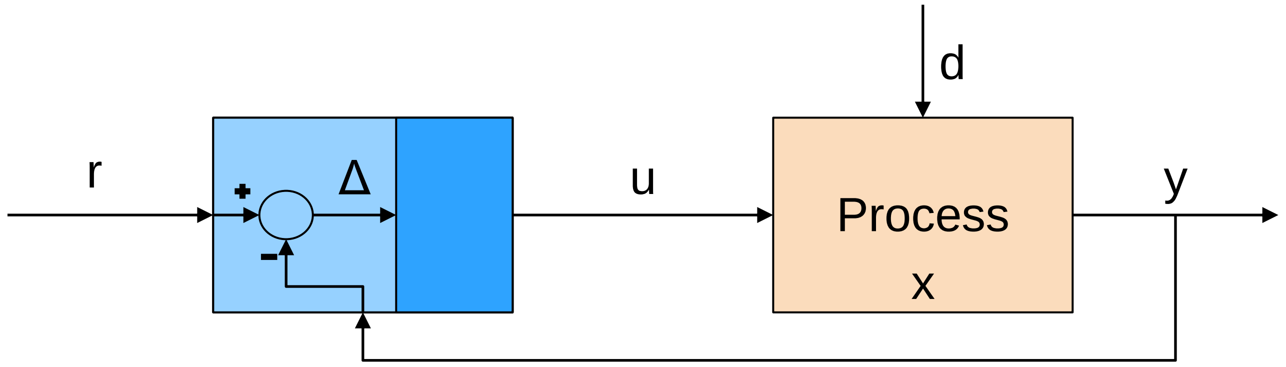
Stability – Some insights (2)

r: reference value
d: disturbance(s)
u: control variable(s)
x: state variable(s)
y: output variable(s)

Open-loop vs. closed loop control



Closed-loop control:

- with feedback
- slower
- the effects of disturbances AND parameter changes of the process are fully compensated
- the loop can become unstable even in case of a stable process

Stability – Some insights (3)

Positive vs. negative feedback

- Positive feedback tends to strengthen the event that caused it (e.g., nuclear reaction)
- Negative feedback tends to reduce the input signal that caused it (e.g., heating control)

All stable feedback is negative

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COMPOSITION OF ADAPTIVE POLICIES

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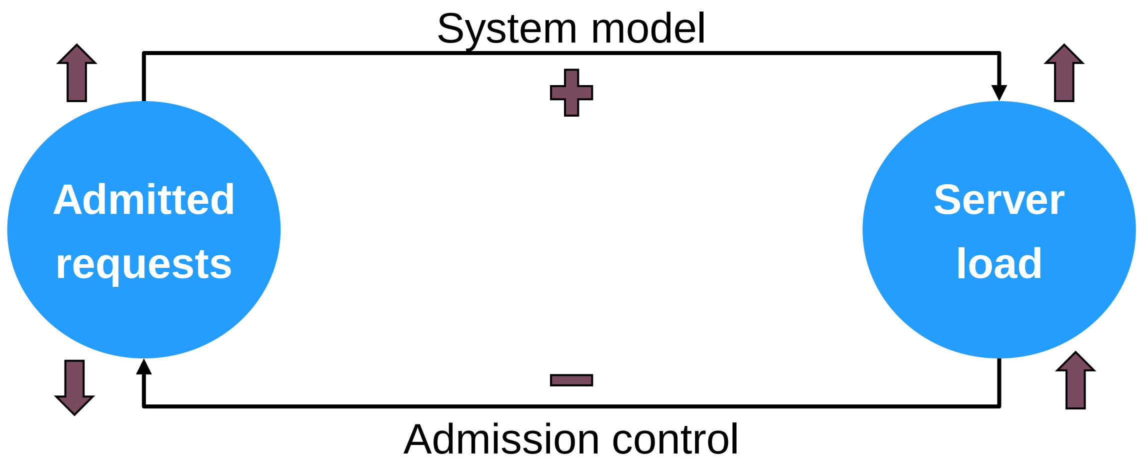
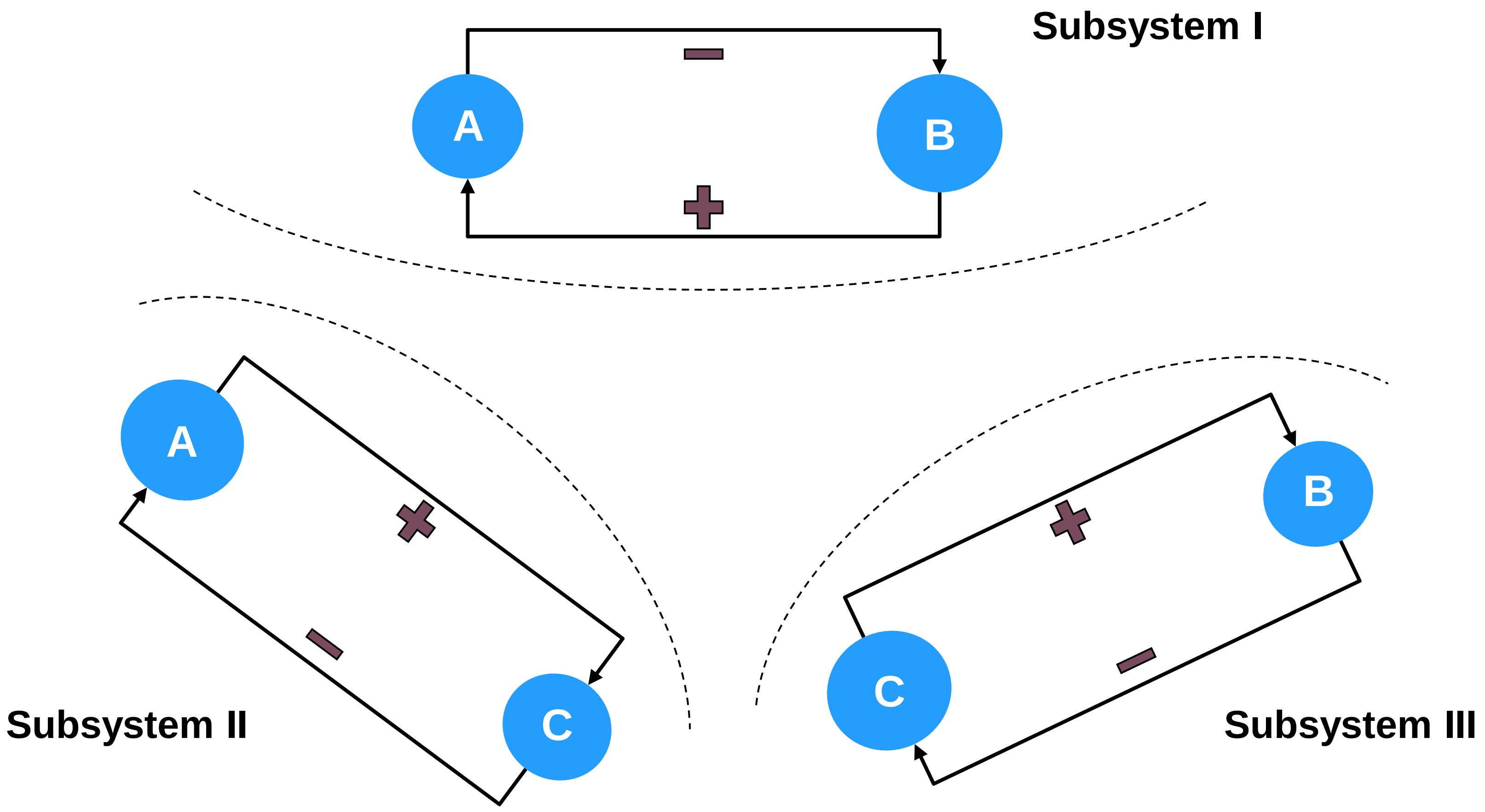
Adaptive policy – a feedback loop



Composition of adaptive subsystems



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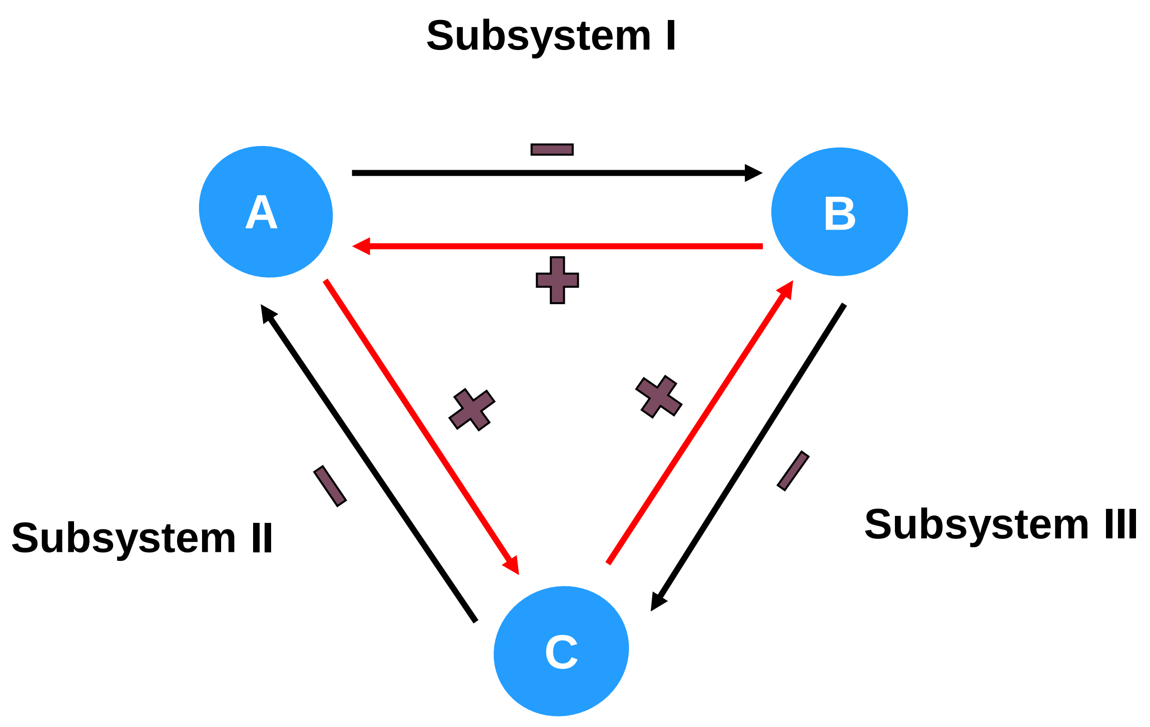
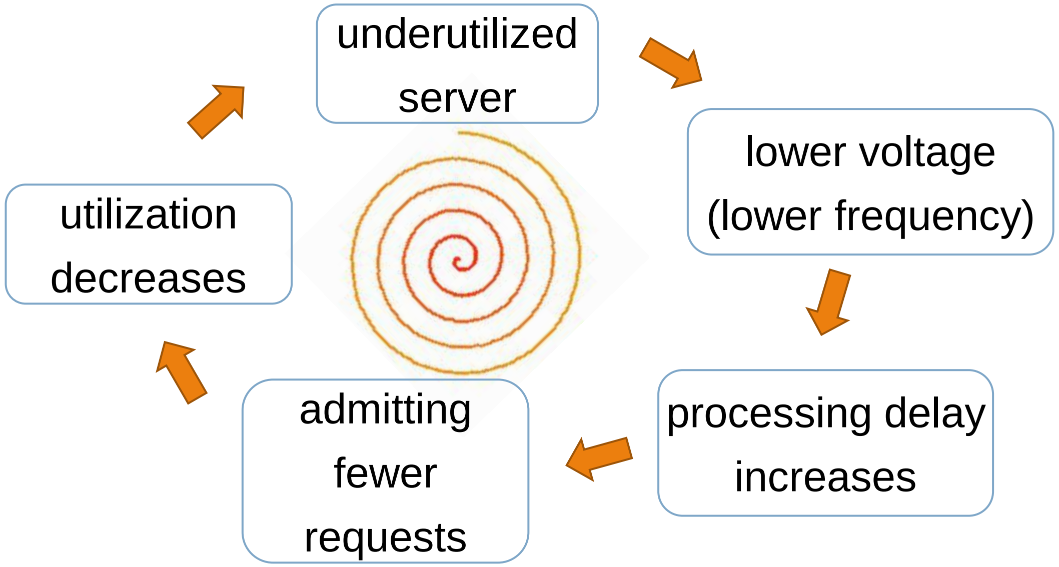
Composition of adaptive subsystems



Adverse policy interactions – an example of a Web server

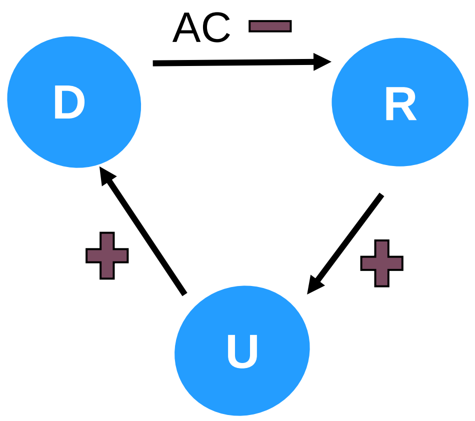
- Dynamic Voltage Scaling (DVS)
  - in an underutilized server, DVS decreases frequency, hence increasing delay
- Admission Control (AC)
  - responds to increased delay by admitting fewer requests



DETECTION OF POSSIBLE CONFLICTS

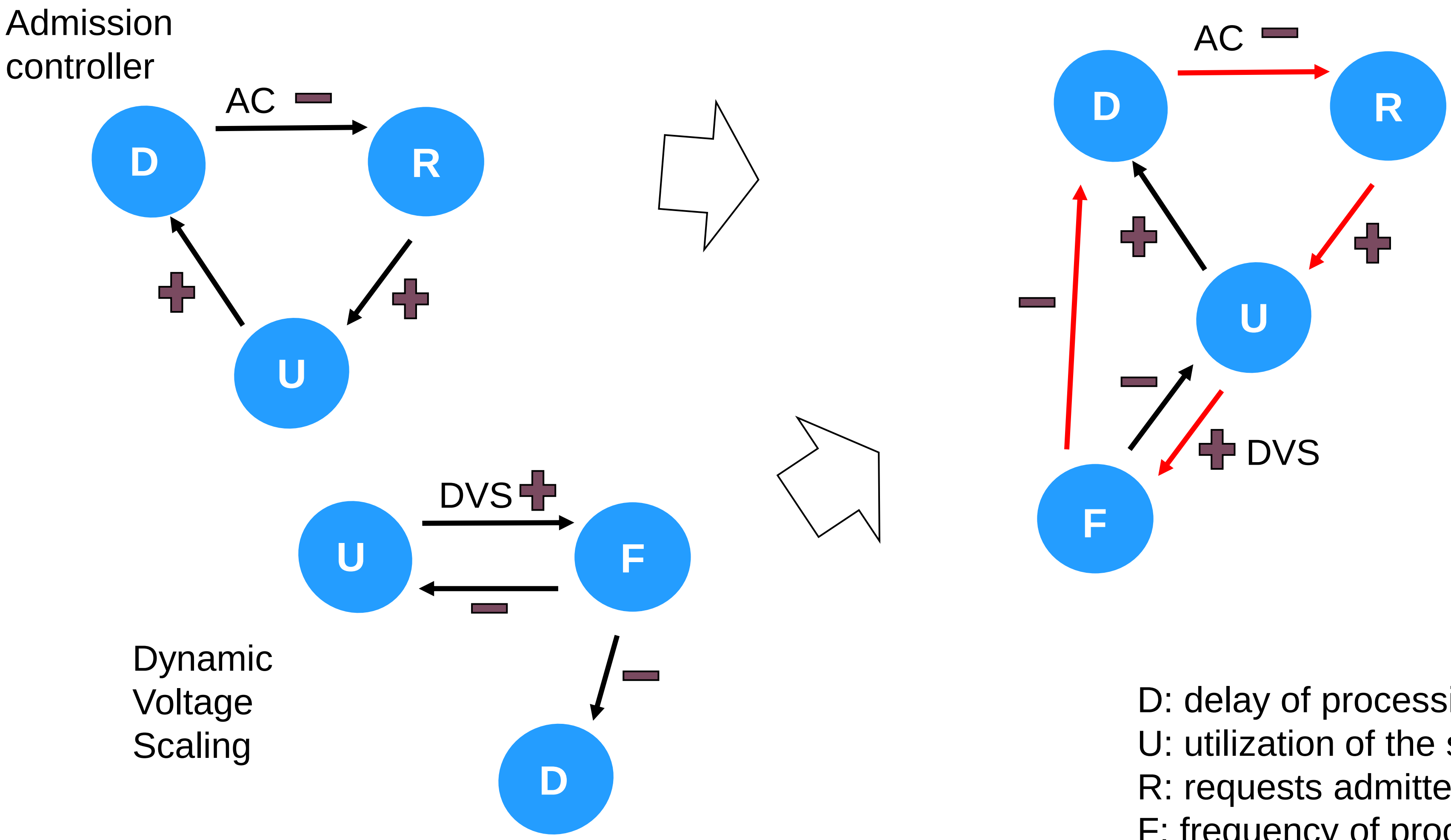
Adaptation Graph Analysis

- Nodes – key variables in the system
- Arcs – direction of causality
  - "+" arcs – changes in the same direction
  - "-" arcs – changes in the opposite direction
  - normal arcs – natural relationship
  - policy arcs – programmed behavior
- Sign of a directed circle – multiplication of the signs of all edges



Adaptation graphs determine which adaptive policies conflict (if they do)

Checks for potential incompatibility



D: delay of processing
U: utilization of the server
R: requests admitted
F: frequency of processing

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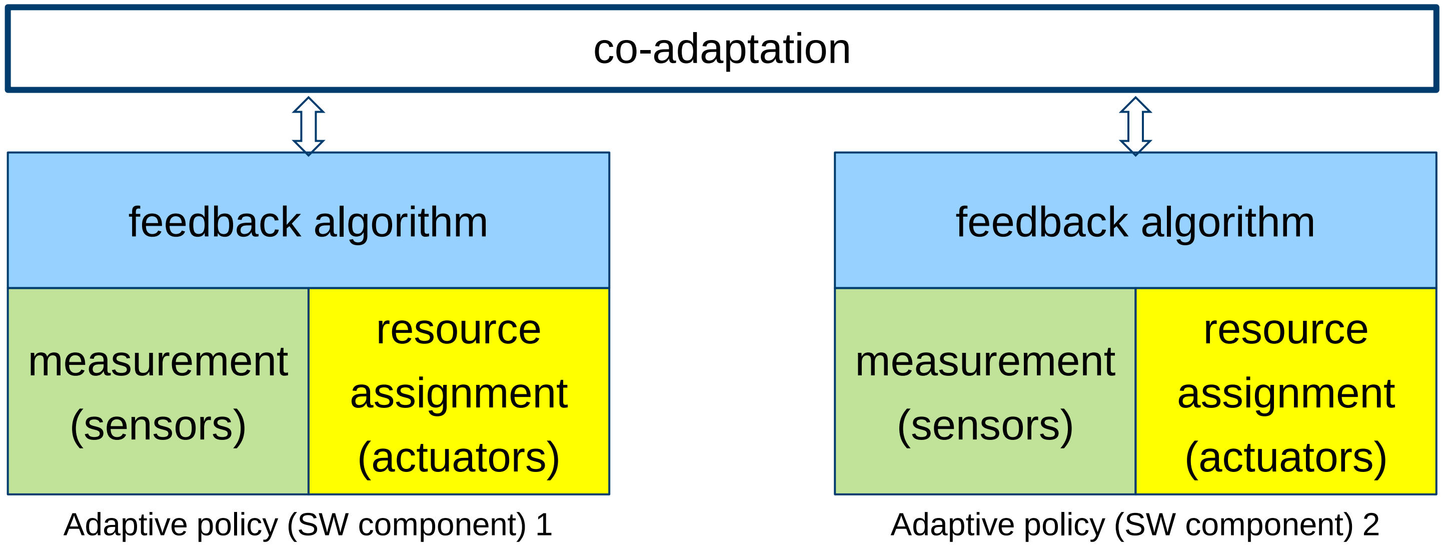
DESIGN METHODOLOGY FOR INTEGRATING ADAPTIVE POLICIES

Co-adaptation


co-adaptation
feedback algorithm
measurement (sensors)
resource assignment (actuators)
Adaptive policy (SW component) 1
feedback algorithm
measurement (sensors)
resource assignment (actuators)
Adaptive policy (SW component) 2

- co-adaptation guides the design of a combined module – it outputs jointly optimized knob settings that increase utility
- constrained optimization (necessary condition) + feedback control

Step 1: Casting the objective

- Find a common objective function – minimize cost or maximize utility
  - Same objective → ok
  - Different objective functions → Find common function

Step 2: Formulating the optimization problem

- Decision variables – settings of adaptation knobs
- Subject to two types of constraints:
  - Performance specifications
  - Resource constraints

$$\begin{aligned} \min_{x_1,\ldots,x_n} \quad & f(x_1,\ldots,x_n) \\ \text{subject to} \quad & g_j(x_1,\ldots,x_n) \leq 0, \quad j = 1,\ldots,m \end{aligned}$$

where f is the common objective function,
x_i are the set of adaptation knobs for policy i (these sets may overlap)
g_j are the constraints

Step 3: Necessity conditions for optimality

- Lack of accurate model for computing systems
- Augmented by feedback loops to move closer to the point that increases utility
- Use the Karush-Kuhn-Tucker (KKT) optimality condition

$$\Gamma x_i \leftarrow \frac{\partial f(x_1,\ldots,x_n)}{\partial x_i} + \sum_{j=1}^{m} \nu_j \frac{\partial g_j(x_1,\ldots,x_n)}{\partial x_i} = 0$$

- Necessary condition:

$$\Gamma_{x_1} = \ldots = \Gamma_{x_n}$$

  - Define $\Gamma_x = (\Gamma_{x_1} + \ldots + \Gamma_{x_n})/n$

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Step 4: Feedback control

- Periodic measurements to estimate Γx_i

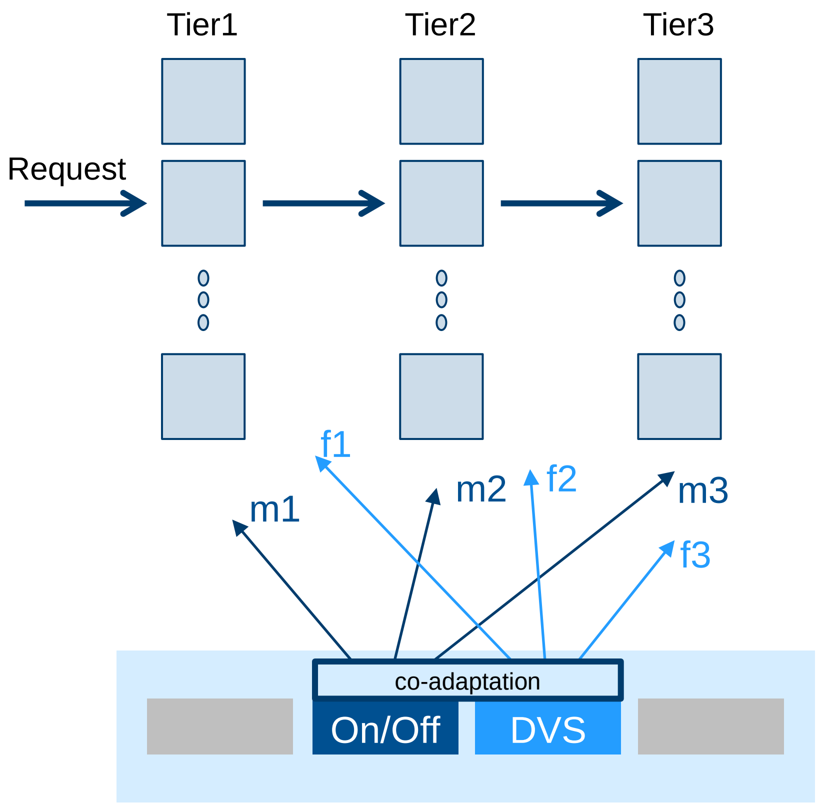
- Try to meet the necessary condition $\Gamma x_1 = \ldots = \Gamma x_n$ by hill climbing
  - Pick one with the largest or smallest value of Γx_i
  - Search through the neighboring knob settings (values of x_i)
    - Reduce the error $\Gamma x - \Gamma x_i$
    - Maximum increase in utility

x_i are the sets of adaptation knobs for policy i

A SERVER FARM CASE STUDY

Energy minimization in server farms

Energy minimization in server farms



- Two adaptive policies in conflict
  - On/Off policy
  - DVS policy
- Co-adaptation finds the knob settings (m1,m2,m3,f1,f2,f3) such that energy consumption is reduced

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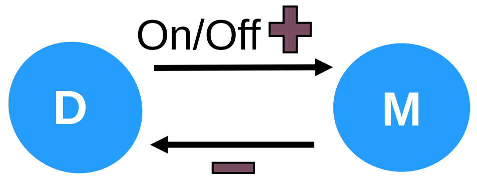
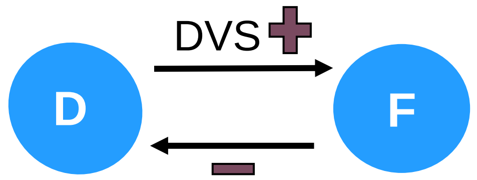
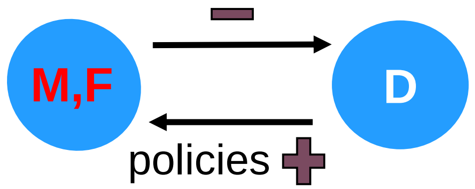
Step 0: Incompatibility detection

On/Off policy



Dynamic Voltage Scaling policy





Combined together, the loop is still negative.

But potentially unstable: possible interference in the control of D!

Step 1: Casting the objective

- In this case, both policies have the objective to minimize energy consumption.
  - Hence, energy is the common cost function

Step 2: Formulating the optimization problem

- Decision variables:
  - Number of active machines in each tier
  - Frequency level of the machines in each tier
    (or, equivalently, the utilization of each tier)
- Approximations:
  - M/M/1 queuing model
  - Number of computers in each tier is a real number
    (relaxation of the integer problem)
  - Power consumption is equal for all machines in a tier
  - Machines are load-balanced (same U, same F) inside the tier

Step 2: Formulating the optimization problem

$$P_i(f_i) = A_i \cdot f_i^p + B_i$$

Power estimation of a machine at tier i

$$U_i = \frac{\lambda}{\mu} = \frac{\lambda_i / m_i}{f_i} = \frac{\lambda_i}{m_i f_i}$$

Queuing equation using number of machines and arrival rate

$$P_i(U_i, m_i) = A_i \cdot \left(\frac{\lambda_i}{U_i m_i}\right)^p + B_i = \frac{A_i \lambda_i^p}{U_i^p m_i^p} + B_i$$

Power estimation function of a machine at tier i

$$\min_{U_i \geq 0,\ m_i \geq 0} \quad P_{tot}(U_i, m_i) = \sum_{i=1}^{3} m_i \left(\frac{A_i \lambda_1^3}{U_i^3 m_i^3} + B_i \right)$$

$$\text{subject to} \quad \sum_{i=1}^{3} \frac{m_i}{\lambda_i} \cdot \frac{U_i}{1 - U_i} \leq K, \qquad \sum_{i=1}^{3} m_i \leq M$$

Formulation of the problem:

find best composition of

$(m_1, m_2, m_3, U_1, U_2, U_3)$

Constraint: end-to-end delay

Constraint: No. of machines in a tier

Step 3: Necessity conditions for optimality

- Karush-Kuhn-Tucker condition

$$\frac{\lambda_1^4(1-U_1)^2}{m_1^3U_1^4} = \frac{\lambda_2^4(1-U_2)^2}{m_2^3U_2^4} = \frac{\lambda_3^4(1-U_3)^2}{m_3^3U_3^4}$$

$$\Gamma(m_1, U_1) = \Gamma(m_2, U_2) = \Gamma(m_3, U_3)$$

Try to find (m_1, m_2, m_3, U_1, U_2, U_3) tuple that balance this condition

Step 4: Feedback control

- Goal: to balance the necessary condition in the direction to reduce energy consumption
- When delay constraint violated
  - Pick the most overloaded tier – the one with lowest $\Gamma(m_i,U_i)$
- Choose (m_i,U_i) pair that makes the error within a bound and yields the lowest total energy
  - Error = $\Gamma_x - \Gamma(m_i,U_i)$, where Γ_x is the average of $\Gamma(m_i,U_i)$

Local control decisions, based on a globally obtained system snapshot

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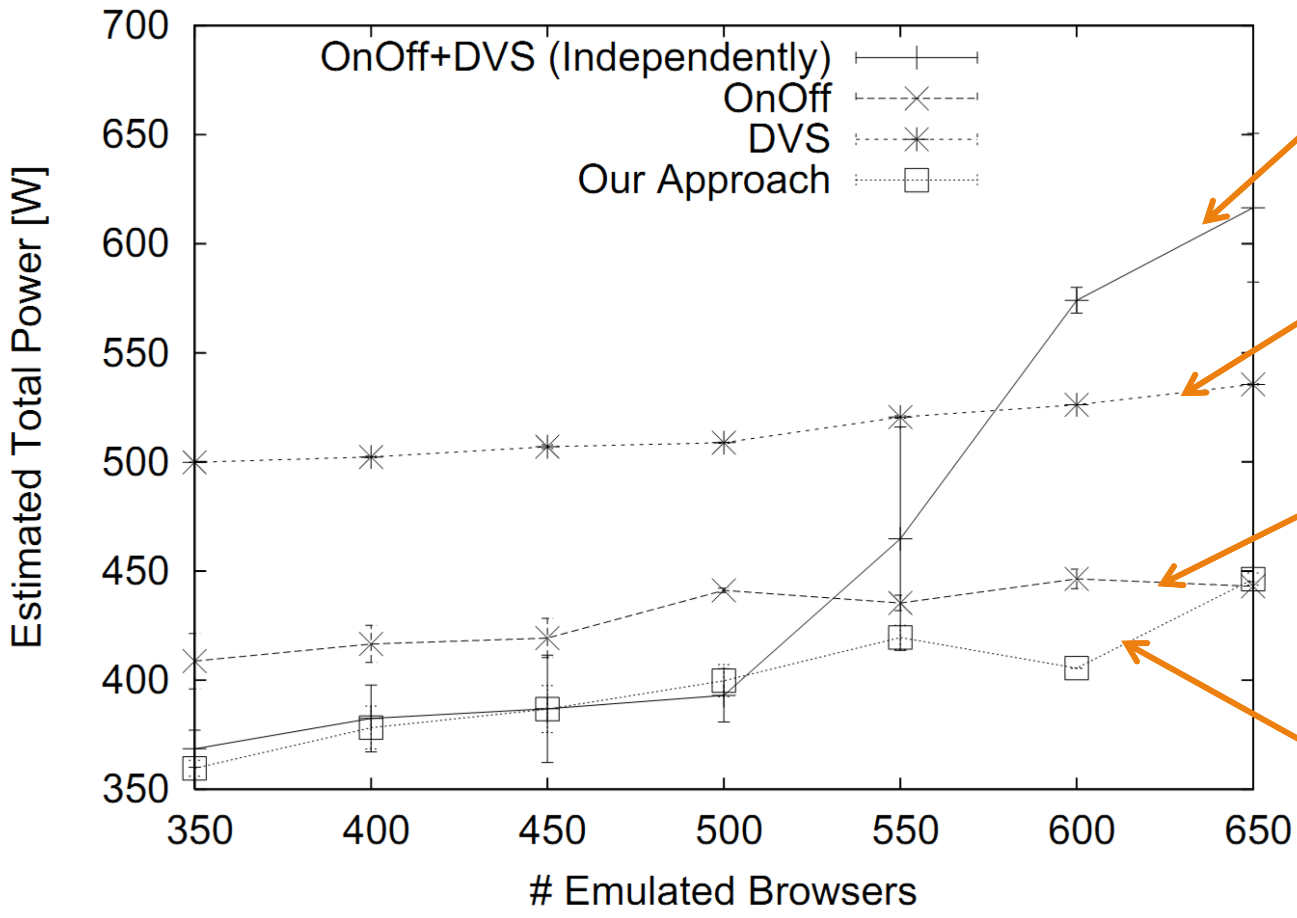
EXPERIMENTAL RESULTS

Evaluation on a 3-tier server farm

Experimental results



DVS + On/Off without co/adaptation: more energy consumption than DVS or On/Off alone!

DVS alone

On/Off alone

Together with co-adaptation: successfully resolves conflict!

Summary

This paper

- presents a simple mechanism for identifying potentially adverse interactions between policies at component composition time,
- describes a methodology for designing co-adaptation, where the adverse interaction is eliminated, and
- evaluates the method with a Web server farm case-study.

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Questions?

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References

[1] Jin Heo, Dan Henriksson, Xue Liu and Tarek Abdelzaher, “Integrating Adaptive Components: An Emerging Challenge in Performance-Adaptive Systems and a Server Farm Case-Study,” *The 28th IEEE Real-Time Systems Symposium (RTSS 07)* December 3-6, 2007, Tucson, Arizona, USA

[2] This presentation contains slides from Tarek Abdelzaher

http://www.docstoc.com/docs/38789686/Integrating-Adaptive-Components-An-Emerging-Challenge-in

[3] Tarek Abdelzaher, “Composition and Scaling Challenges in Sensor Networks: an Interaction-Centric View,” *Chapter 1 in S. Nikoletseas, J.D.P. Rolim (eds.) – Theoretical Aspects of Distributed Computing in Sensor Networks, Springer, 2011*