

# Controller design for networks of switching servers

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Queueing Colloquium  
November 21, 2008, CWI

# Acknowledgements

This work was supported by the Netherlands Organization for Scientific Research (NWO-VIDI grant 639.072.072).

Inspired by discussions with:

- Varvara Feoktistova, Alexey Matveev (St. Petersburg)
- Jan van der Wal, Josine Bruin
- Stefan Lämmer (TU Dresden)
- Gideon Weiss, Yoni Nazarathy (Haifa)

# Motivation



# Problem

## Problem

How to control these networks?

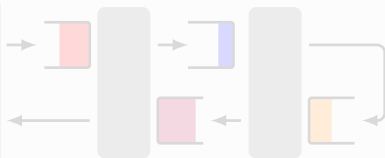
Decisions: **When** to switch, and **to which** job-type

Goals: Minimal number of jobs, minimal flow time

## Current approach

Start from **policy**, analyze resulting dynamics

## Kumar, Seidman (1990)



Clearing



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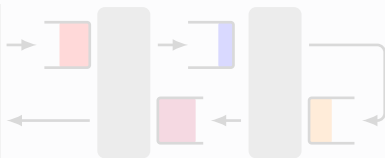
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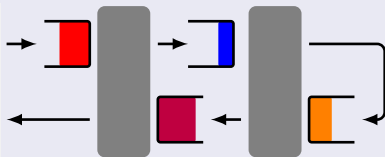
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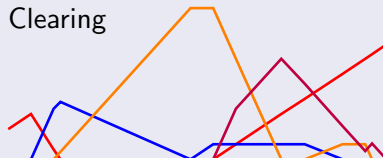
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# Problem

## Current status (after two decades)

Several policies exist that guarantee **stability** of the network

## Remark

Stability is **only a prerequisite** for a good policy

## Open issues

- Do existing policies yield satisfactory network performance?
- How to obtain pre-specified network behavior?

## Main subject of study (modest)

Fixed, deterministic flow networks (not evolving, constant inflow)

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# Approach



## Approach

Use ideas/concepts from control theory

# Background: Control theory

## System dynamics (linear)

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t) & x &\in R^n, u \in R^k \\ y(t) &= Cx(t) & y &\in R^m\end{aligned}$$

where  $u(\cdot)$  is a **function** to be designed.

## Problem I: Trajectory generation

Determine feasible functions  $x_r(t)$ ,  $u_r(t)$ .

## Problem II: State feedback tracking control

Given **arbitrary** feasible  $x_r(t)$ ,  $u_r(t)$ , find a controller  $u(\cdot)$ , such that

$$\lim_{t \rightarrow \infty} \|x(t) - x_r(t)\| = 0.$$

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# Background: Control theory, Example tracking control

## Controller

$$u = u_r + K(x - x_r)$$

## Error dynamics

Define  $e = x - x_r$ , then:

$$\dot{e} = Ax + B(u_r + Ke) - (Ax_r + Bu_r) = (A + BK)e$$

Make sure that  $K$  is such that eigenvalues of  $A + BK$  are in left half of complex plane.

## Remark

The controller design holds for **arbitrary** reference.

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Reconstruct  $x$  using only measurement of  $y$

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# Background: Control theory, Example observer design

## Observer

$$\begin{aligned}\dot{\hat{x}} &= A\hat{x} + Bu + L(y - \hat{y}) \\ \hat{y} &= C\hat{x}\end{aligned}$$

## Observer error dynamics

Define  $e = x - \hat{x}$ , then

$$\dot{e} = A\hat{x} + Bu + LCe - (Ax + Bu) = (A + LC)e$$

Make sure that  $L$  is such that eigenvalues of  $A + LC$  are in left half of complex plane.

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## Dynamic output feedback tracking controller

$$\begin{aligned}u &= u_r + K(\hat{x} - x_r) \\ \dot{\hat{x}} &= A\hat{x} + Bu(t) + L(y - \hat{y}) \\ \hat{y} &= C\hat{x}\end{aligned}$$

where  $K$  and  $L$  from previous designs can be used.

# Approach

## Notions from control theory

- 1 Generate feasible **reference** trajectory
- 2 Design (static) **state feedback** controller
- 3 Design **observer**
- 4 Design (dynamic) **output feedback** controller

## Parallels with this problem

- 1 Determine desired system behavior
- 2 Derive non-distributed/centralized controller
- 3 Can state be reconstructed?
- 4 Derive distributed/decentralized controller



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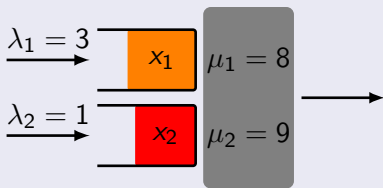
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# Example 1: Single machine

## Single machine

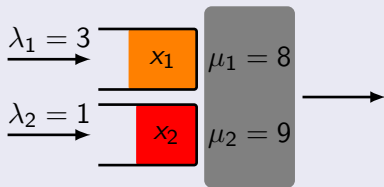
$$\sigma_{12} = 3, \sigma_{21} = 1$$



# Example 1: Single machine

## Single machine

$$\sigma_{12} = 3, \sigma_{21} = 1$$



## State

- $x_0$  remaining setup time
- $x_i$  buffer contents ( $i = 1, 2$ )
- $m$  mode  $\in \{1, 2\}$

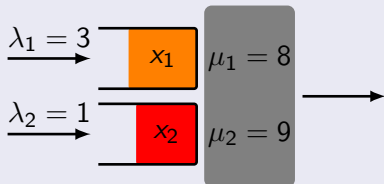
## Input

- $u_0$  activity  $\in \{\textcircled{1}, \textcircled{2}, \textcircled{1}, \textcircled{2}\}$
- $u_i$  service rate step  $i = 1, 2$

# Example 1: Single machine

## Single machine

$$\sigma_{12} = 3, \sigma_{21} = 1$$



## Continuous dynamics

$$\dot{x}_0(t) = \begin{cases} -1 & \text{if } u_0 \in \{\textcircled{1}, \textcircled{2}\} \\ 0 & \text{if } u_0 \in \{\textcircled{1}, \textcircled{2}\} \end{cases}$$

$$\dot{x}_1(t) = \lambda_1 - u_1(t)$$

$$\dot{x}_2(t) = \lambda_2 - u_2(t)$$

## Discrete event dynamics

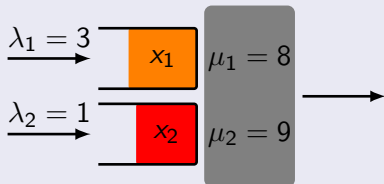
$$x_0 := \sigma_{21} \quad m := 1 \quad \text{if } u_0 = \textcircled{1} \text{ and } m = 2$$

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$$u_0 \in \{ \textcircled{1}, \textcircled{2} \} \quad u_1 = 0 \quad u_2 = 0 \quad \text{if } x_0 > 0$$

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## Objective

Minimize:

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \int_0^t x_1(\tau) + x_2(\tau) d\tau \quad \text{or} \quad \frac{1}{T} \int_0^T x_1(\tau) + x_2(\tau) d\tau$$

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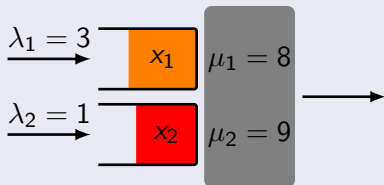
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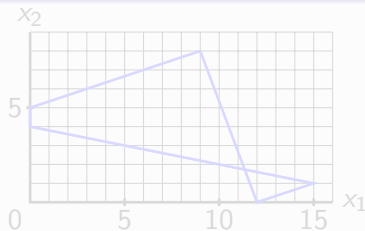
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## Single machine



## Desired behavior



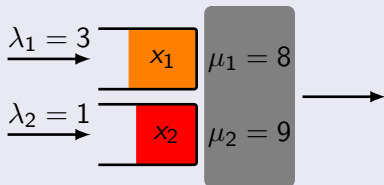
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- Many existing policies assume **non-idling** a-priori
- Slow-mode optimal if  $\lambda_1(\frac{\lambda_1}{\mu_1} + \frac{\lambda_2}{\mu_2}) - (\lambda_1 - \lambda_2)(1 - \frac{\lambda_2}{\mu_2}) < 0$ .
- Trade-off in wasting capacity: **idle**  $\Leftrightarrow$  **switch more often**

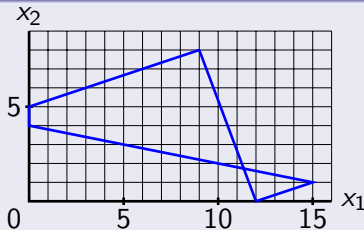


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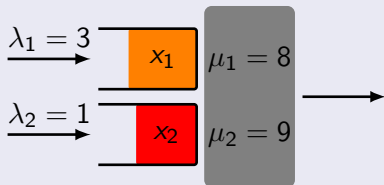


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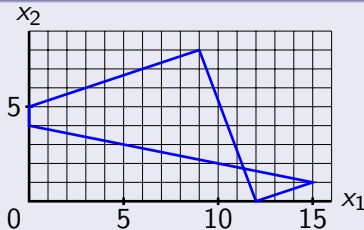
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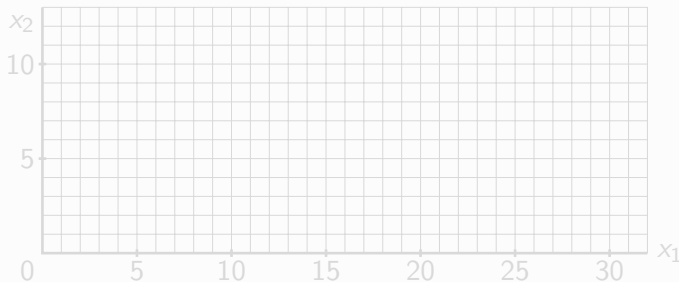
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Lyapunov: if energy is decreasing all the time  $\Rightarrow$  system settles down at constant energy level

## Lyapunov function candidate

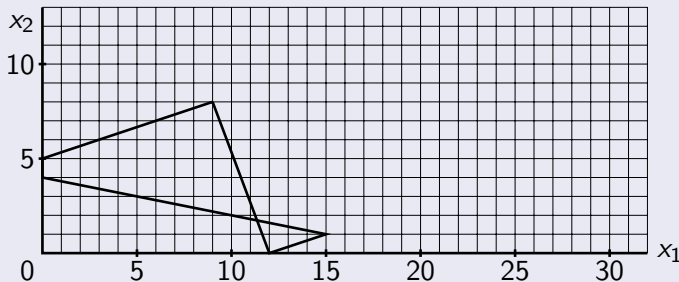


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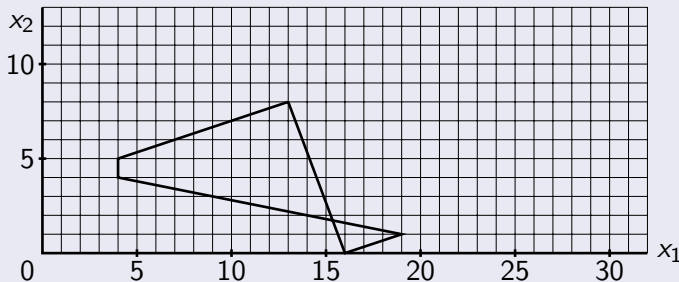


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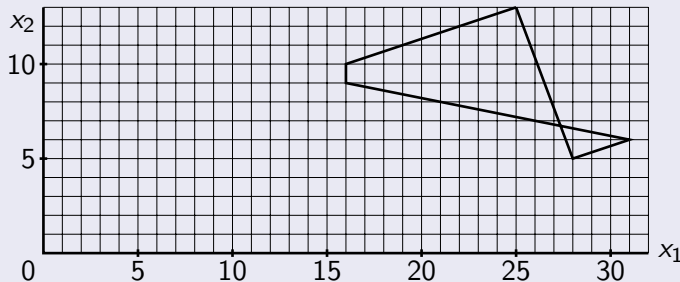


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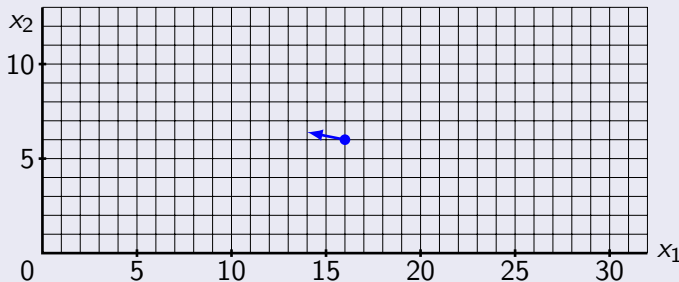


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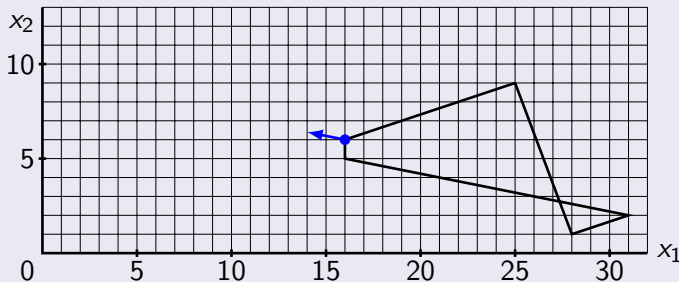


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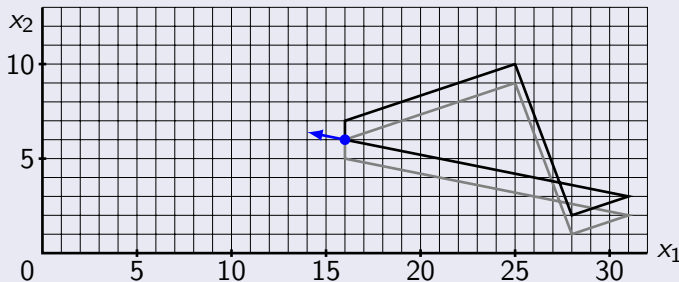


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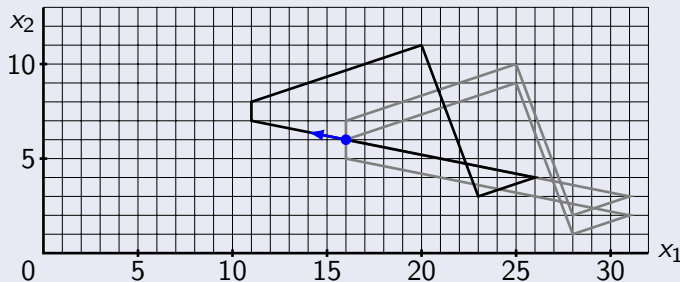


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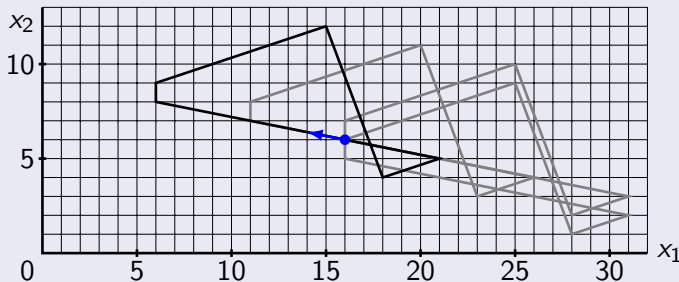


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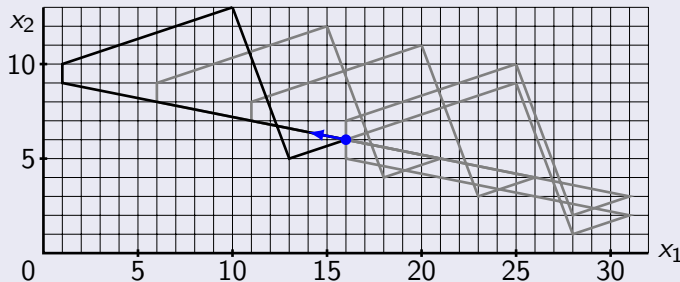


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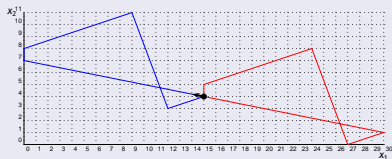


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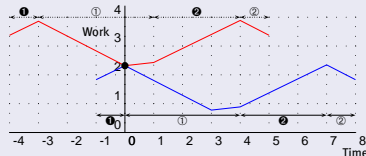
## Lyapunov function candidate

The smallest **additional mean amount of work** from all feasible curves for state (work:  $x_1/\mu_1 + x_2/\mu_2$ ).

## Phase plane



## Time evolution work



## Controller design

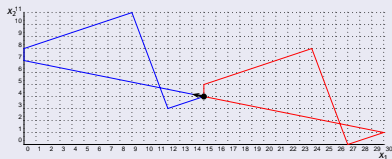
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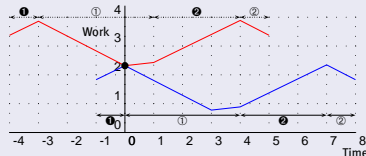
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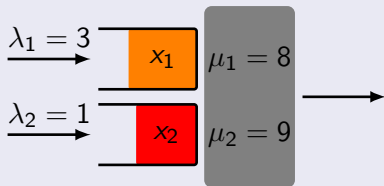


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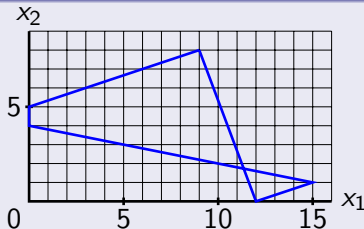
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# Controller design (Result)

## Single machine



## Desired behavior



## Resulting Controller, cf. [Lefeber, Rooda (2006)]

- When serving type 1:

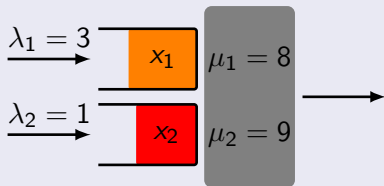
- empty buffer
- serve until  $x_2 \geq 5$
- switch to type 2

- When serving type 2:

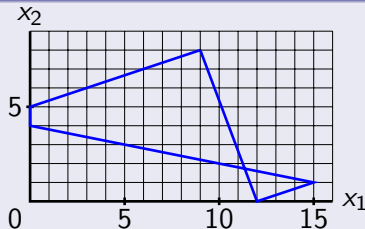
- empty buffer
- serve until  $x_1 \geq 12$
- switch to type 1

# Controller design (Result)

## Single machine



## Desired behavior



## Resulting Controller, cf. [Lefeber, Rooda (2006)]

- When serving type 1:

- ① empty buffer
- ② serve until  $x_2 \geq 5$
- ③ switch to type 2

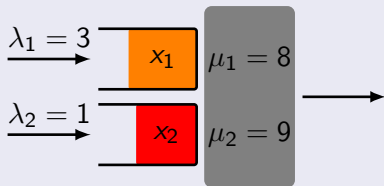
- When serving type 2:

- ① empty buffer
- ② serve until  $x_1 \geq 12$
- ③ switch to type 1

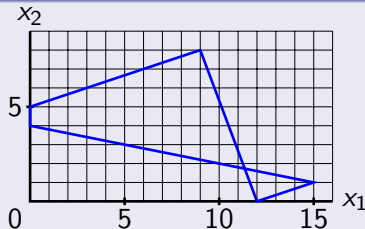


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- When serving type 1:
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  - ② serve until  $x_1 \geq 12$
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# Recap

## Notions from control theory

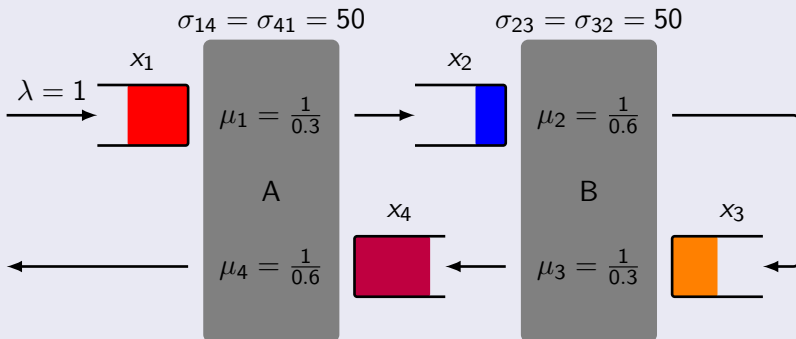
- 1 Generate feasible **reference** trajectory
- 2 Design (static) **state feedback** controller
- 3 Design **observer**
- 4 Design (dynamic) **output feedback** controller

## Parallels with this problem

- 1 Determine desired system behavior
- 2 Derive non-distributed/centralized controller
- 3 Can state be reconstructed?
- 4 Derive distributed/decentralized controller

## Example 2: Kumar-Seidman case

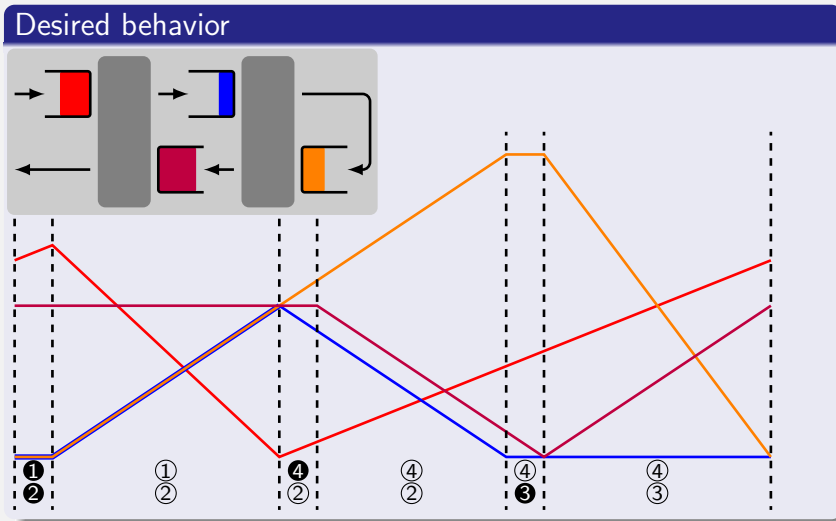
Transactions on Automatic Control, Vol 35, No 3, March 1990



### Observation

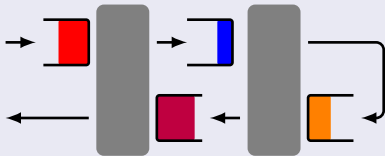
Sufficient capacity (consider period of at least 1000).

# Desired behavior

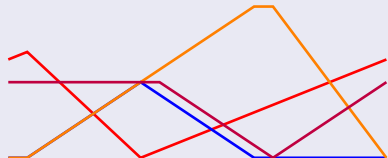


# Resulting controller

## Network



## Desired behavior



## Resulting controller

Mode (1,2): to (4,2) when both  $x_1 = 0$  and  $x_2 + x_3 \geq 1000$

Mode (4,2): to (4,3) when both  $x_2 = 0$  and  $x_4 \leq 83\frac{1}{3}$

Mode (4,3): to (1,2) when  $x_3 = 0$

Remark:

- Non-distributed/centralized controller

# Proof

## Monodromy operator

$x_i^k$ : buffer contents at  $k^{\text{th}}$  start of mode (1,2). For  $k > 2$ :

$$\begin{aligned} x_1^{k+1} &= 50 + \frac{3}{7}(x_1^k + 50) + \max\left(\frac{3}{7}(x_1^k + 50), \frac{3}{5}x_4^k\right) \\ x_2^{k+1} &= 0 \quad x_3^{k+1} = 0 \quad x_4^{k+1} = \frac{5}{7}(x_1^k + 50) \end{aligned} \quad (1)$$

## Observation

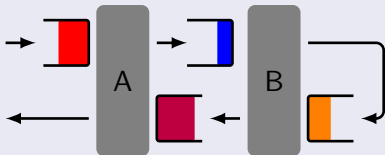
With  $y_1^k = (x_1^k - 650)/7$ ,  $y_4^k = (x_4^k - 500)/5$  we get from (1):

$$0 \leq \max(y_1^{k+2}, y_4^{k+2}) \leq \frac{6}{7} \max(y_1^k, y_4^k)$$

So system converges to fixed point (650, 0, 0, 500).

# Observability

## Network



## Assumptions

- Clearing policy used for machine B
- At  $t = t_1$ : ③ starts
- At  $t = t_2 > t_1$ : ③ stops

System state can be reconstructed at machine A

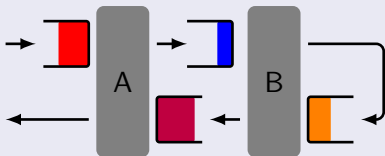
- $x_3(t_2) = 0$ , and  $0.3(t_2 - t_1) = x_3(t_1) = x_3(t_1 - 50)$
- $x_2(t_1 - 50) = 0$ , and  $x_2(t_2) = \int_{t_1-50}^{t_2} u_1(\tau) d\tau$

## Observation

Observability determined by network topology

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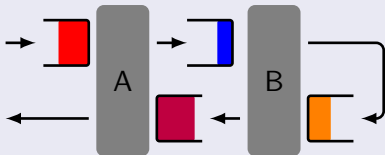
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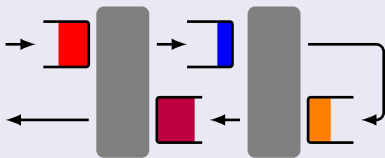
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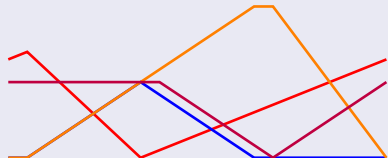
Observability determined by network topology

# Distributed controller, cf. [Lefebvre, Rooda (2008)]

## Network



## Desired behavior



## Distributed controller

**Serving 1:** Serve at least 1000 jobs until  $x_1 = 0$ , then **switch**.  
Let  $\bar{x}_1$  be nr of jobs served.

**Serving 4:** Let  $\bar{x}_4$  be nr of jobs in Buffer 4 after setup. Serve  $\bar{x}_4 + \frac{1}{2}\bar{x}_1$  jobs, then **switch**.

**Serving 2:** Serve at least 1000 jobs until  $x_2 = 0$ , then **switch**.

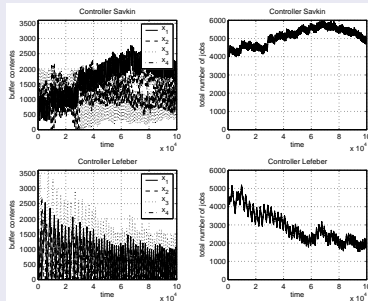
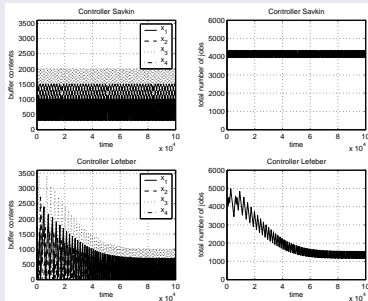
**Serving 3:** Empty buffer, then **switch**.

# Simulation results

Initial condition (1000, 1000, 1000, 1000).

Deterministic/Exponential service times, setup times.

## Distributed controller



# Conclusions

## New approach

- 1 Determine desired system behavior (**trajectory generation**)
- 2 Derive non-distributed/centralized controller (**state feedback**)
- 3 Derive distributed/decentralized controller (**output feedback**)

## Advantage

All three problems can be considered **separately**

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Approach can deal with

- Arbitrary networks
- Finite buffers
- Transportation delays

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- Observer based approach results in new, tailor-made controllers that perform better

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# Future work

## Research

- Centralized control
  - Finalize techniques for convergence proofs
  - Derive class of controllers (instead of only one)
  - Finite buffers: reachability of desired orbit
  - Deal with parametric uncertainty; robustness if parameters are either different or time-varying.
- Decentralized control (!!PhD vacancy!!)
  - Observability (including tests)
  - Observer design
  - Stability analysis of distributed policies
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# Adaptive control

## System dynamics

$$\dot{x} = ax + u \quad a \text{ unknown parameter}$$

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$$u = -\hat{a}x - kx \quad k > 0$$

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$$\lim_{t \rightarrow \infty} x(t) = 0$$

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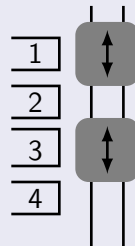
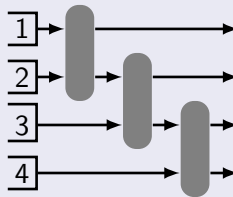
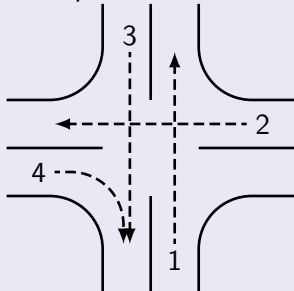
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# System

## System

Server can serve several queues **simultaneously**, each queue at rate  $\mu_i$ , independent of the number of queues being served.

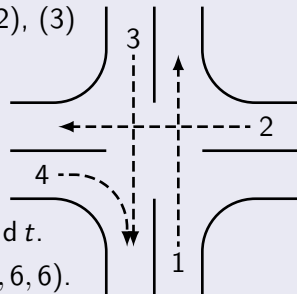
### Examples



# Problem

## Example

- Modes: (1,4), (2,4), (1,3), (4), (1), (2), (3)
- Deterministic fluid queues
- No arrivals, i.e.  $\lambda_i = 0$
- $\mu_i = 1$
- Objective: minimize
$$\int_0^\infty 4x_1(t) + 3x_2(t) + 2x_3(t) + 5x_4(t) dt.$$
- Initial condition  $(x_1, x_2, x_3, x_4) = (6, 6, 6, 6)$ .



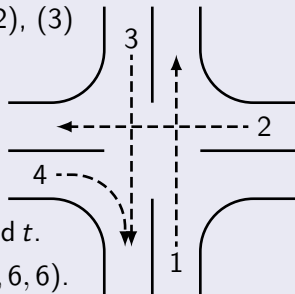
## Possible policies

- Mode (1,4) for 6, Mode (2) for 6, Mode (3) for 6: costs 504.
- Mode (2,4) for 6, Mode (1,3) for 6: costs 468.
- Optimal costs: 456.

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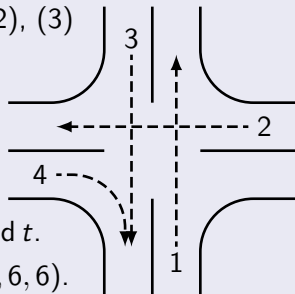
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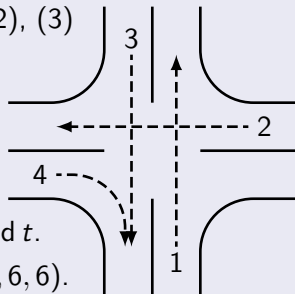
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# Optimal controller

**Initialization:** Start in Mode (1,4).

**Mode (1,4):** Stay in mode until either  $x_1 = 0$ , or  $x_4 = 0$ , or  $x_4 \leq x_2 \wedge x_1 \leq x_3 \wedge (\mu_1 c_1 - \mu_2 c_2 + \mu_3 c_3) \left( \frac{x_1}{\mu_1} + \frac{x_4}{\mu_4} \right) \leq \mu_3 c_3 \left( \frac{x_2}{\mu_2} + \frac{x_3}{\mu_3} \right)$  then switch to Mode (2,4).

**Mode (2,4):** Stay in mode until either  $x_2 = 0$  or  $x_4 = 0$ , then switch to Mode (1,3).

**Mode (1,3):** Stay in mode until either  $x_1 = 0$  or  $x_3 = 0$ , then switch to Mode (4).

**Mode (4):** Stay in mode until  $x_4 = 0$ , then switch to Mode (1).

**Mode (1):** Stay in mode until  $x_1 = 0$ , then switch to Mode (2).

**Mode (2):** Stay in mode until  $x_2 = 0$ , then switch to Mode (3).

**Mode (3):** Stay in mode until  $x_3 = 0$ .

# With arrival rates

## Some observations

- Can be formulated as SCLP (NO setup times)
- Combined modes
- $\mu c$ -like rule (only for NO setup times)
- Stability conditions (odd cycle graph)
- Setup times: no  $\mu c$ -like rule:

$$c = (0.34, 0.33, 0.32, 0.35)^T \quad x_0 = (30, 20, 20, 40)$$

No arrivals

$\mu c$  rule: (1,4), (2,4), (1,3), 3: costs 1039.68

optimal: (2,4), (1,4), (1,3), 3: costs 1039.60