

# Scalable Control of Positive Systems

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# Wind Farms Need Control

Picture from [http://www.hochtief.com/hochtief\\_en/9164.jhtml](http://www.hochtief.com/hochtief_en/9164.jhtml)



Most wind farms today are paid to maximize power production.  
Future farms will have to curtail power at contracted levels.

New control objective:

Minimize fatigue loads subject to fixed total production.

# Minimizing Fatigue Loads

## Single turbine control:

Minimize tower pressure variance subject to linearized dynamics with measurements of pitch angle and rotor speed.

Optimal controller:  $u_i^{\text{loc}}(t)$

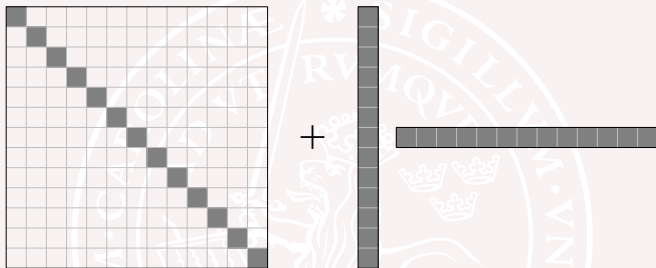
## Wind farm control:

Minimize sum of all tower pressure variances subject to *fixed total production of the farm*:  $\sum_{i=1}^m u_i = 0$

Optimal controller:  $u_i(t) = u_i^{\text{loc}}(t) - \frac{1}{m} \sum_{j=1}^m u_j^{\text{loc}}(t)$ .

[PhD thesis by Daria Madjidian, Lund University, June 2014]

# Controller Structure



Linear quadratic control of  $m$  identical systems and a constraint  $\sum_{i=1}^m u_i = 0$  gives an optimal feedback matrix with two parts:

- One is localized (diagonal).
- The other has rank one (control of the average state).

# Server Farms Need Control

Picture from <http://www.dawn.com/news/1017980>



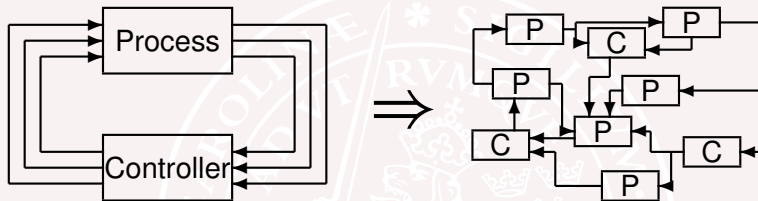
## **Single server control:**

Assign resources (processor speed, memory, etc.) to minimize variance in completion time.

## **Server farm control:**

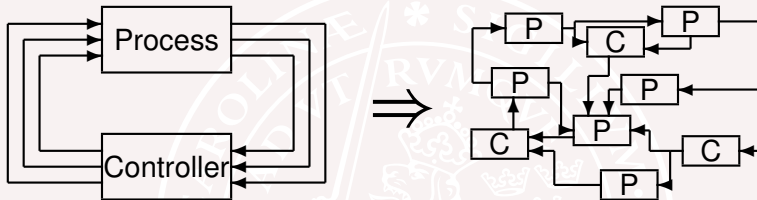
Minimize sum of all time variances with *fixed total resources*.

# Towards a Scalable Control Theory



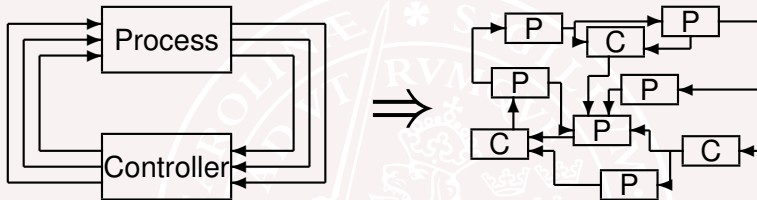
- Linear quadratic control uses  $O(n^3)$  flops,  $O(n^2)$  memory
- Model Predictive Control requires even more
- **Today:** Exploiting monotone/positive systems

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# Outline

- **Positive and Monotone Systems**
  - Scalable Stability Analysis
  - Input-Output Performance
  - Trajectory Optimization
  - Combination Therapy for HIV and Cancer

# Positive systems

A linear system is called *positive* if the state and output remain nonnegative as long as the initial state and the inputs are nonnegative:

$$\frac{dx}{dt} = Ax + Bu \quad y = Cx$$

Equivalently,  $A$ ,  $B$  and  $C$  have nonnegative coefficients except for the diagonal of  $A$ .

## Examples:

- Probabilistic models.
- Economic systems.
- Chemical reactions.
- Ecological systems.

# Positive Systems and Nonnegative Matrices

## Classics:

**Mathematics:** Perron (1907) and Frobenius (1912)

**Economics:** Leontief (1936)

## Books:

**Nonnegative matrices:** Berman and Plemmons (1979)

**Dynamical Systems:** Luenberger (1979)

## Recent control related work:

**Biology inspired theory:** Angeli and Sontag (2003)

**Synthesis by linear programming:** Rami and Tadeo (2007)

**Switched systems:** Liu (2009), Fornasini and Valcher (2010)

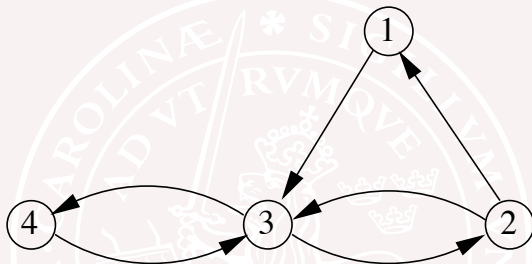
**Distributed control:** Tanaka and Langbort (2010)

**Robust control:** Briat (2013)

# Example 1: Transportation Networks

- Cloud computing / server farms
- Heating and ventilation in buildings
- Traffic flow dynamics
- Production planning and logistics

# A Transportation Network is a Positive System



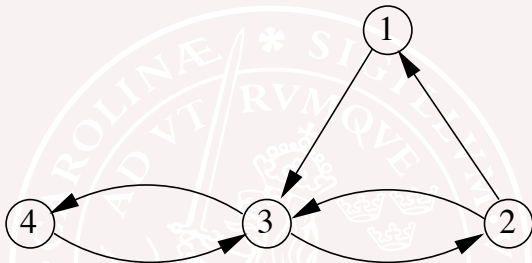
$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} -1 - l_{31} & l_{12} & 0 & 0 \\ 0 & -l_{12} - l_{32} & l_{23} & 0 \\ l_{31} & l_{32} & -l_{23} - l_{43} & l_{34} \\ 0 & 0 & l_{43} & -4 - l_{34} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix}$$

How do we select  $l_{ij}$  to minimize the gain from  $w$  to  $x$ ?

## Example 2: A vehicle formation



## Example 2: Vehicle Formations



$$\begin{cases} \dot{x}_1 = -x_1 + \ell_{13}(x_3 - x_1) + w_1 \\ \dot{x}_2 = \ell_{21}(x_1 - x_2) + \ell_{23}(x_3 - x_2) + w_2 \\ \dot{x}_3 = \ell_{32}(x_2 - x_3) + \ell_{34}(x_4 - x_3) + w_3 \\ \dot{x}_4 = -4x_4 + \ell_{43}(x_3 - x_4) + w_4 \end{cases}$$

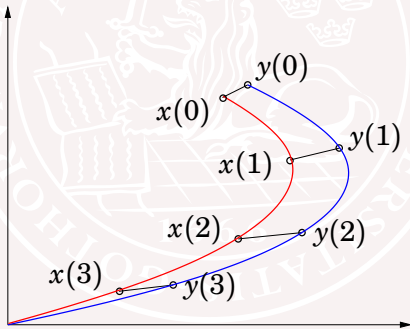
How do we select  $\ell_{ij}$  to minimize the gain from  $w$  to  $x$ ?

# Nonlinear Monotone Systems

The system

$$\dot{x}(t) = f(x(t), u(t)), \quad x(0) = a$$

is a *monotone system* if its linearization is a positive system.





# Macroscopic Models of Traffic Flow

- 1 Partial differential equation by Lighthill/Whitham (1955), Richards (1956) based on mass-conservation:

$$0 = \frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x} f(\rho)$$

where  $\rho(x, t)$  is traffic density in position  $x$  at time  $t$  and  $f(\rho)$  expresses flow as function of density.

- 2 Spatial discretization by Daganzo (1994).

Both models are monotone systems!

Exploited for lines: [Gomes/Horowitz/Kurzhanskiy/Varaiya/Kwon, 2008].  
Exploited for networks: [Lovisari/Como/Rantzer/Savla, MTNS-14].

# Outline

- Positive and Monotone Systems
- **Scalable Stability Analysis**
- Input-Output Performance
- Trajectory Optimization
- Combination Therapy for HIV and Cancer

# Stability of Positive systems

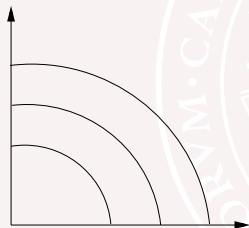
Suppose the matrix  $A$  has nonnegative off-diagonal elements. Then the following conditions are equivalent:

- (i) The system  $\frac{dx}{dt} = Ax$  is exponentially stable.
- (ii) There is a *diagonal* matrix  $P \succ 0$  such that  $A^T P + PA \prec 0$
- (iii) There exists a vector  $\xi > 0$  such that  $A\xi < 0$ .  
(The vector inequalities are elementwise.)
- (iv) There exists a vector  $z > 0$  such that  $A^T z < 0$ .

# Lyapunov Functions of Positive systems

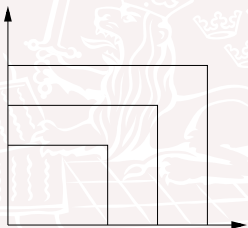
Solving the three alternative inequalities gives three different Lyapunov functions:

$$A^T P + P A < 0$$



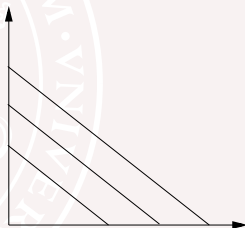
$$V(x) = x^T P x$$

$$A \xi < 0$$



$$V(x) = \max_k (x_k / \xi_k)$$

$$A^T z < 0$$



$$V(x) = z^T x$$

# A Scalable Stability Test



Stability of  $\dot{x} = Ax$  follows from existence of  $\xi_k > 0$  such that

$$\underbrace{\begin{bmatrix} a_{11} & a_{12} & 0 & a_{14} \\ a_{21} & a_{22} & a_{23} & 0 \\ 0 & a_{32} & a_{33} & a_{34} \\ a_{41} & 0 & a_{43} & a_{44} \end{bmatrix}}_A \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \end{bmatrix} < \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

The first node verifies the inequality of the first row.

The second node verifies the inequality of the second row.

...

*Verification is scalable!*

# A Distributed Search for Stabilizing Gains

Suppose  $\begin{bmatrix} a_{11} - \ell_1 & a_{12} & 0 & a_{14} \\ a_{21} + \ell_1 & a_{22} - \ell_2 & a_{23} & 0 \\ 0 & a_{32} + \ell_2 & a_{33} & a_{32} \\ a_{41} & 0 & a_{43} & a_{44} \end{bmatrix} \geq 0$  for  $\ell_1, \ell_2 \in [0, 1]$ .

For stabilizing gains  $\ell_1, \ell_2$ , find  $0 < \mu_k < \xi_k$  such that

$$\begin{bmatrix} a_{11} & a_{12} & 0 & a_{14} \\ a_{21} & a_{22} & a_{23} & 0 \\ 0 & a_{32} & a_{33} & a_{32} \\ a_{41} & 0 & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \end{bmatrix} + \begin{bmatrix} -1 & 0 \\ 1 & -1 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} < \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

and set  $\ell_1 = \mu_1/\xi_1$  and  $\ell_2 = \mu_2/\xi_2$ . Every row gives a local test.  
Distributed synthesis by linear programming (gradient search).

# Max-separable Lyapunov Functions

Let  $\dot{x} = f(x)$  be a monotone system such that the origin globally asymptotically stable and the compact set  $X \subset \mathbb{R}_+^n$  is invariant. Then there exist strictly increasing functions

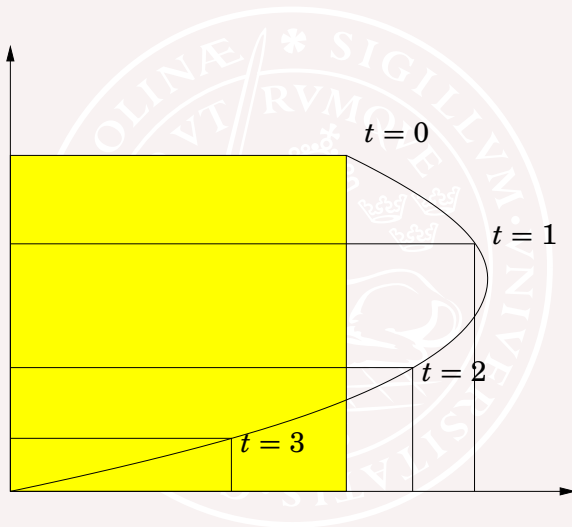
$V_k : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  for  $k = 1, \dots, n$ , such that  $V(x) = \max\{V_1(x_1), \dots, V_n(x_n)\}$  satisfies

$$\frac{d}{dt}V(x(t)) = -V(x(t))$$

along all trajectories in  $X$ .

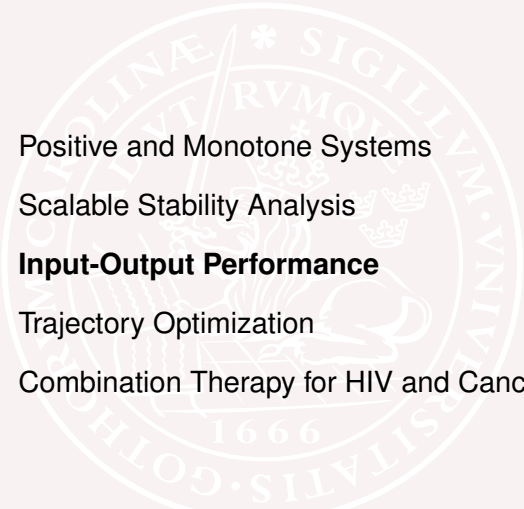
[Rantzer, Rüffer, Dirr, CDC-13]

# Proof idea





# Outline

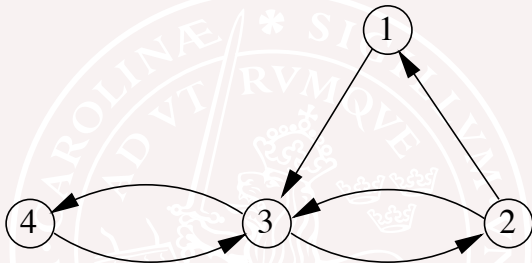
- 
- Positive and Monotone Systems
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  - **Input-Output Performance**
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# Performance of Positive systems

Suppose that  $\mathbf{G}(s) = C(sI - A)^{-1}B + D$  where  $A \in \mathbb{R}^{n \times n}$  is Metzler, while  $B \in \mathbb{R}_+^{n \times 1}$ ,  $C \in \mathbb{R}_+^{1 \times n}$  and  $D \in \mathbb{R}_+$ . Define  $\|\mathbf{G}\|_\infty = \sup_\omega |G(i\omega)|$ . Then the following are equivalent:

- (i) The matrix  $A$  is Hurwitz and  $\|\mathbf{G}\|_\infty < \gamma$ .
- (ii) The matrix  $\begin{bmatrix} A & B \\ C & D - \gamma \end{bmatrix}$  is Hurwitz.

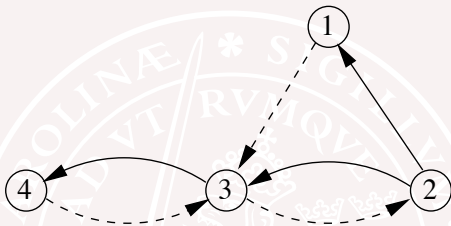
# Example 1: Transportation Networks



$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} -1 - \ell_{31} & \ell_{12} & 0 & 0 \\ 0 & -\ell_{12} - \ell_{32} & \ell_{23} & 0 \\ \ell_{31} & \ell_{32} & -\ell_{23} - \ell_{43} & \ell_{34} \\ 0 & 0 & \ell_{43} & -4 - \ell_{34} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} w \\ w \\ w \\ w \end{bmatrix}$$

How do we select  $\ell_{ij} \in [0, 1]$  to minimize the gain from  $w$  to  $\sum_i x_i$ ?

# Example 1: Transportation Networks



Minimize  $\sum_i \xi_i$  subject to

$$0 \geq -\xi_1 - \mu_{31} + \mu_{12} + 1$$

$$0 \geq -\mu_{12} - \mu_{32} + \mu_{23} + 1$$

$$0 \geq \mu_{31} + \mu_{32} - \mu_{23} - \mu_{43} + \mu_{34} + 1$$

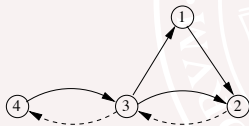
$$0 \geq -4\xi_4 + \mu_{43} - \mu_{34} + 1$$

and  $0 \leq \mu_{ij} \leq \xi_j$ . Then define  $\ell_{ij} = \mu_{ij}/\xi_j$ .

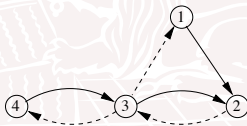
Optimal solution  $\ell_{12} = \ell_{32} = \ell_{43} = 1$  and  $\ell_{31} = \ell_{23} = \ell_{34} = 0$ .

## Example 2: Vehicle Formations

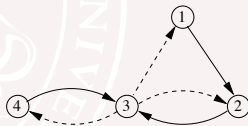
$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} -1 - \ell_{13} & 0 & \ell_{13} & 0 \\ \ell_{21} & -\ell_{21} - \ell_{23} & \ell_{23} & 0 \\ 0 & \ell_{32} & -\ell_{32} - \ell_{34} & \ell_{34} \\ 0 & 0 & \ell_{43} & -4 - \ell_{43} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + Bw$$



$$B = \begin{bmatrix} 10 \\ 10 \\ 1 \\ 1 \end{bmatrix}$$



$$B = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$



$$B = \begin{bmatrix} 1 \\ 1 \\ 10 \\ 10 \end{bmatrix}$$

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- Positive and Monotone Systems
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# Convex-Monotone Systems

The system

$$\dot{x}(t) = f(x(t), u(t)), \quad x(0) = a$$

is a *monotone system* if its linearization is a positive system. It is a *convex monotone system* if every row of  $f$  is also convex.

**Theorem.** [Rantzer/ Bernhardsson (2014)]

For a convex monotone system  $\dot{x} = f(x, u)$ , each component of the trajectory  $\phi_t(a, u)$  is a convex function of  $(a, u)$ .

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# Combination Therapy is a Control Problem

Evolutionary dynamics:

$$\dot{x} = \left( A - \sum_i u_i D^i \right) x$$

Each state  $x_k$  is the concentration of a mutant. (There can be hundreds!) Each input  $u_i$  is a drug dosage.

$A$  describes the mutation dynamics without drugs, while  $D^1, \dots, D^m$  are diagonal matrices modeling drug effects.

Determine  $u_1, \dots, u_m \geq 0$  with  $u_1 + \dots + u_m \leq 1$  such that  $x$  decays as fast as possible!

[Hernandez-Vargas, Colaneri and Blanchini, JRNC 2011]

[Jonsson, Rantzer, Murray, ACC 2014]

# Optimizing Decay Rate

Stability of the matrix  $A - \sum_i u_i D^i + \gamma I$  is equivalent to existence of  $\xi > 0$  with

$$(A - \sum_i u_i D^i + \gamma I)\xi < 0$$

For row  $k$ , this means

$$A_k \xi - \sum_i u_i D_k^i \xi_k + \gamma \xi_k < 0$$

or equivalently

$$\frac{A_k \xi}{\xi_k} - \sum_i u_i D_k^i + \gamma < 0$$

Maximizing  $\gamma$  is convex optimization in  $(\log \xi_i, u_i, \gamma)$  !

# Using Measurements of Virus Concentrations

Evolutionary dynamics:

$$\dot{x}(t) = \left( A - \sum_i u_i(t) D^i \right) x(t)$$

Can we get faster decay using time-varying  $u(t)$  based on measurements of  $x(t)$  ?

# Using Measurements of Virus Concentrations

The evolutionary dynamics can be written as a convex monotone system:

$$\frac{d}{dt} \log x_k(t) = \frac{A_k x(t)}{x_k(t)} - \sum_i u_i(t) D_k^i$$

Hence the decay of  $\log x_k$  is a convex function of the input and optimal trajectories can be found even for large systems.

# Example

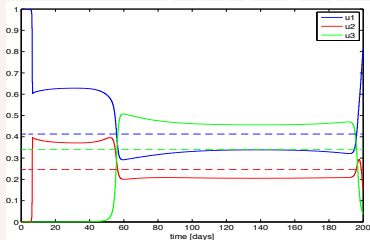
$$A = \begin{bmatrix} -\delta & \mu & \mu & 0 \\ \mu & -\delta & 0 & \mu \\ \mu & 0 & -\delta & \mu \\ 0 & \mu & \mu & -\delta \end{bmatrix}$$

clearance rate  $\delta = 0.24 \text{ day}^{-1}$ , mutation rate  $\mu = 10^{-4} \text{ day}^{-1}$   
and replication rates for viral variants and therapies as follows

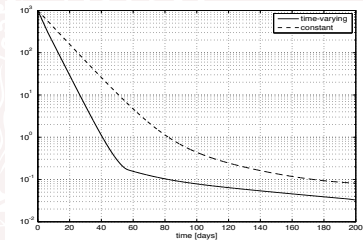
Variant	Therapy 1	Therapy 2	Therapy 3
Wild type ( $x_1$ )	$D_1^1 = 0.05$	$D_1^2 = 0.10$	$D_1^3 = 0.30$
Genotype 1 ( $x_2$ )	$D_2^1 = 0.25$	$D_2^2 = 0.05$	$D_2^3 = 0.30$
Genotype 2 ( $x_3$ )	$D_3^1 = 0.10$	$D_3^2 = 0.30$	$D_3^3 = 0.30$
HR type ( $x_4$ )	$D_4^1 = 0.30$	$D_4^2 = 0.30$	$D_4^3 = 0.15$

# Example

Optimized drug doses:

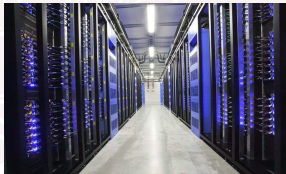


Total virus population:



# For Scalable Control — Use Positive Systems!

- Verification and synthesis scale linearly
- Distributed controllers by linear programming
- No need for global information
- Optimal trajectories by convex optimization



# Many Research Challenges Remain

- Optimal Dynamic Controllers in Positive Systems
- Analyze Trade-off Between Performance and Scalability
- Distributed Controllers for Nonlinear Monotone Systems





# Thanks!



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Vanessa  
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Madjidian



Martina  
Maggio



Alessandro  
Papadopoulos



Bo  
Bernhardsson



Fredrik  
Magnusson