

# Sparsity-promoting Optimal Control of Spatially Invariant Systems

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# Outline

## ① PROBLEM FORMULATION

- ★ **Sparsity promoting  $H_2$  control**
- ★ **Efficient computation for spatially invariant systems**

## ② OPTIMIZATION ALGORITHM

- ★ **Alternating direction method of multipliers**
- ★ **Structured optimal control problem**

## ③ EXAMPLES AND SCALING

- ★ **Linear computational complexity in the number of subsystems**

# State-feedback $H_2$ problem

$$\dot{x} = Ax + B_1d + B_2u$$

$$u = -Fx$$

- CLOSED-LOOP  $H_2$  NORM

$$J(F) := \lim_{t \rightarrow \infty} \mathcal{E} (x^T(t)Qx(t) + u^T(t)Ru(t))$$

- OPTIMAL STATE FEEDBACK GAIN

$$A^T P + PA + Q - PB_2R^{-1}B_2^T P = 0$$

$$F = R^{-1}B_2^T P$$

★  $F$  is in general a dense matrix

# Sparsity-promoting $H_2$ problem

- ADD SPARSITY REQUIREMENTS

$$\begin{array}{ccc}
 \text{minimize} & J(F) & + \gamma \text{card}(F) \\
 & \downarrow & \downarrow \\
 & \text{optimize} & \text{promote} \\
 & \text{performance} & \text{sparsity}
 \end{array}$$

*Lin, Fardad, Jovanović, IEEE TAC '13*

- CHALLENGES

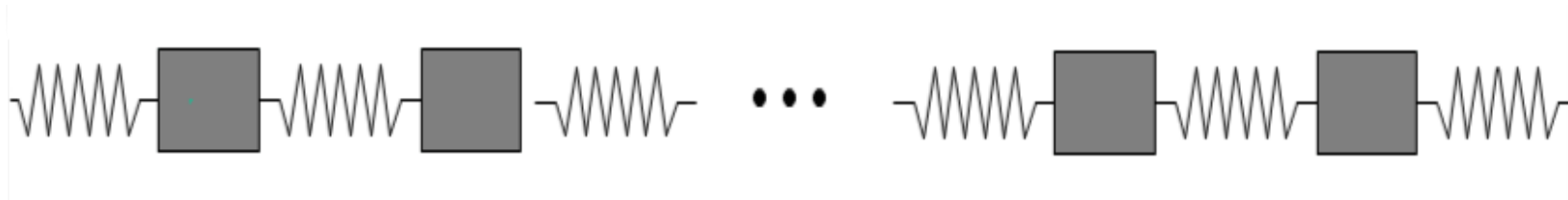
- ★ **non-convex objective function**
- ★ **computationally complex for large systems**

$$\mathcal{O}(N^3 m^3)$$

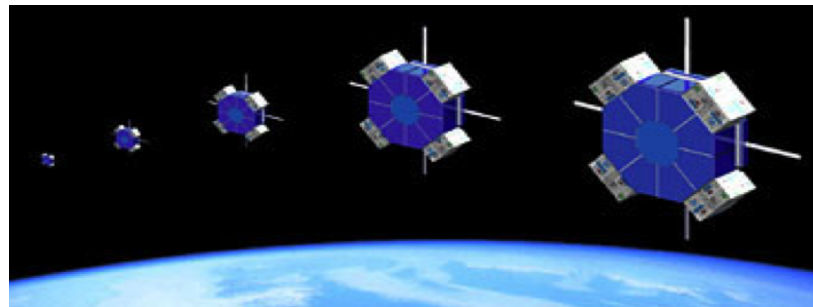
- \*  $N$  - number of subsystems
- \*  $m$  - number of states per subsystem

# Spatially-invariant systems

- TRADEOFF GENERALITY FOR PERFORMANCE
  - ★ restrict method to spatially-invariant systems
  - ★ develop more efficient method
- EXAMPLES
  - ★ infinite mass-spring system



- ★ satellite system



# Spatially-invariant systems

- APPLY DISCRETE FOURIER TRANSFORM

$$\begin{aligned}\dot{\hat{x}} &= \hat{A}\hat{x} + \hat{B}_1\hat{d} + \hat{B}_2\hat{u} \\ \hat{u} &= -\hat{F}\hat{x}\end{aligned}$$

$$\hat{F} = \Phi F \Phi^*$$

- DECOUPLE  $H_2$  NORM

$$J(\hat{F}) = \sum_{i=1}^N J_i(\hat{F}_i) = \sum_{i=1}^N \text{trace} \left( \hat{P}_i \hat{B}_{1i} \hat{B}_{1i}^T \right)$$

- ★ computational complexity of solving Riccati equation

$$\mathcal{O}(Nm^3)$$

- ★ linear in the number of subsystems  $N$

# Sparsity-promoting $H_2$ problem

- ADDITIONAL REQUIREMENTS ON GAIN

★ **promote sparsity**

- OPTIMIZATION PROBLEM

$$\text{minimize} \quad J(\hat{F}) \quad + \quad \gamma \sum_{i,j} W_{ij} |F_{ij}|$$

$\downarrow$   

**Fourier domain:  
optimize performance**

$\downarrow$   

**physical domain:  
promote sparsity**

$g(F) \rightarrow$  convex relaxation of **card**( $F$ )

# Alternating direction method of multipliers

- INTRODUCE CONSTRAINT

$$\begin{aligned} & \text{minimize} && J(\hat{F}) + \gamma g(F) \\ & \text{subject to} && \hat{F} - \Phi F \Phi^* = 0 \end{aligned}$$

★ exploit structure in both domains

- FORM AUGMENTED LAGRANGIAN

$$\mathcal{L}_\rho(\hat{F}, F, \Lambda) = J(\hat{F}) + \gamma g(F) + \text{trace}(\Lambda^T(\hat{F} - \Phi F \Phi^*)) + \frac{\rho}{2} \|\hat{F} - \Phi F \Phi^*\|_F^2$$



# Alternating direction method of multipliers

- Solve optimization problem using sequence of iterations (ADMM):

## 1. Optimize performance

$$\hat{F}^{k+1} := \arg \min_{\hat{F}} \mathcal{L}_\rho(\hat{F}, F^k, \Lambda^k)$$

★ in Fourier domain

## 2. Promote sparsity

$$F^{k+1} := \arg \min_F \mathcal{L}_\rho(\hat{F}^{k+1}, F, \Lambda^k)$$

★ in physical domain

## 3. Update Lagrange multiplier

$$\Lambda^{k+1} := \Lambda^k + \rho(\hat{F}^{k+1} - \Phi F^{k+1} \Phi^*)$$

## Performance optimization step

$$\text{minimize } J(\hat{F}) + (\rho/2)\|\hat{F} - \hat{U}^k\|_F^2$$

$$\hat{U}^k := \Phi F^k \Phi^* - (1/\rho)\Lambda^k$$

- DECOUPLE PROBLEM

$$\text{minimize } \sum_{i=1}^N \left( J_i(\hat{F}_i) + (\rho/2)(\hat{F}_i - \hat{U}_i^k)^2 \right)$$

- EFFICIENCY GAIN

- ★ solve Lyapunov equations for each block

*Lin, Fardad, Jovanović, IEEE TAC '13*

$$\mathcal{O}(Nm^3)$$

- ★ add subsystem → solve one more set of Lyapunov equations

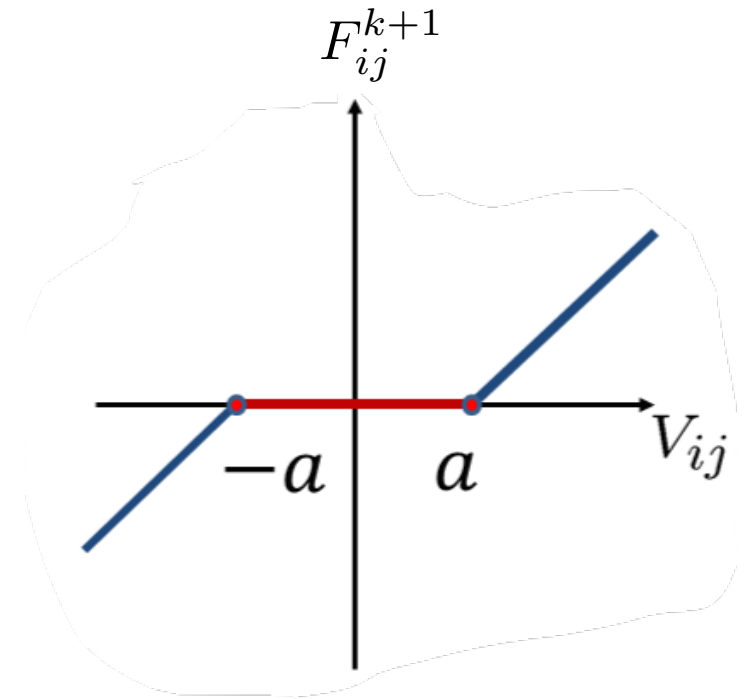
## Sparsity-promoting step

$$\text{minimize } \gamma g(F) + (\rho/2) \|F - V^k\|_F^2$$

$$V^k := \hat{F}^{k+1} + (1/\rho)\Lambda^k$$

- SOLUTION: SOFT-THRESHOLDING OPERATOR

$$F_{ij}^{k+1} = \begin{cases} (1 - a/\|V_{ij}\|_F)V_{ij}, & \|V_{ij}\|_F > a \\ 0, & \|V_{ij}\|_F \leq a \end{cases}$$



$$\star a = (\gamma/\rho)W_{ij}$$

# Structured optimal control problem

- OPTIMIZE IDENTIFIED STRUCTURE

$$\begin{aligned} & \text{minimize} && J(\hat{F}) \\ & \text{subject to} && \hat{F} - \Phi F \Phi^* = 0, \quad F \in \mathcal{S} \end{aligned}$$

$\mathcal{S} \rightarrow$  subspace of sparsity patterns identified via ADMM

- REWRITE WITH INDICATOR FUNCTION  $\phi$

$$\begin{aligned} & \text{minimize} && J(\hat{F}) + \phi(F) \\ & \text{subject to} && \hat{F} - \Phi F \Phi^* = 0 \end{aligned}$$

# Solving structured optimal control problem using ADMM

- PERFORMANCE OPTIMIZATION STEP
- STRUCTURE ENFORCEMENT STEP

$$\begin{aligned} & \text{minimize} && \frac{\rho}{2} \|F - V^k\|_F^2 \\ & \text{subject to} && F \in \mathcal{S} \end{aligned}$$

$$V^k = \hat{F}^{k+1} + (1/\rho)\Lambda^k$$

## ★ Solution

$$F^{k+1} = V^k \circ I_{\mathcal{S}}$$

$I_{\mathcal{S}}$  - structural identity

$$F = \begin{bmatrix} * & * & & \\ * & * & * & \\ & * & * & * \\ & & * & * \end{bmatrix} \Rightarrow I_{\mathcal{S}} = \begin{bmatrix} 1 & 1 & & \\ 1 & 1 & 1 & \\ & 1 & 1 & 1 \\ & & 1 & 1 \end{bmatrix}$$

# EXAMPLES

# First-order system with $N = 5$ nodes distributed over a circle

- SYSTEM DYNAMICS:

$$A = \begin{bmatrix} -2 & 1 & 0 & 0 & 1 \\ 1 & -2 & 1 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & -2 & 1 \\ 1 & 0 & 0 & 1 & -2 \end{bmatrix}$$

$$B_1 = B_2 = Q = R = I$$

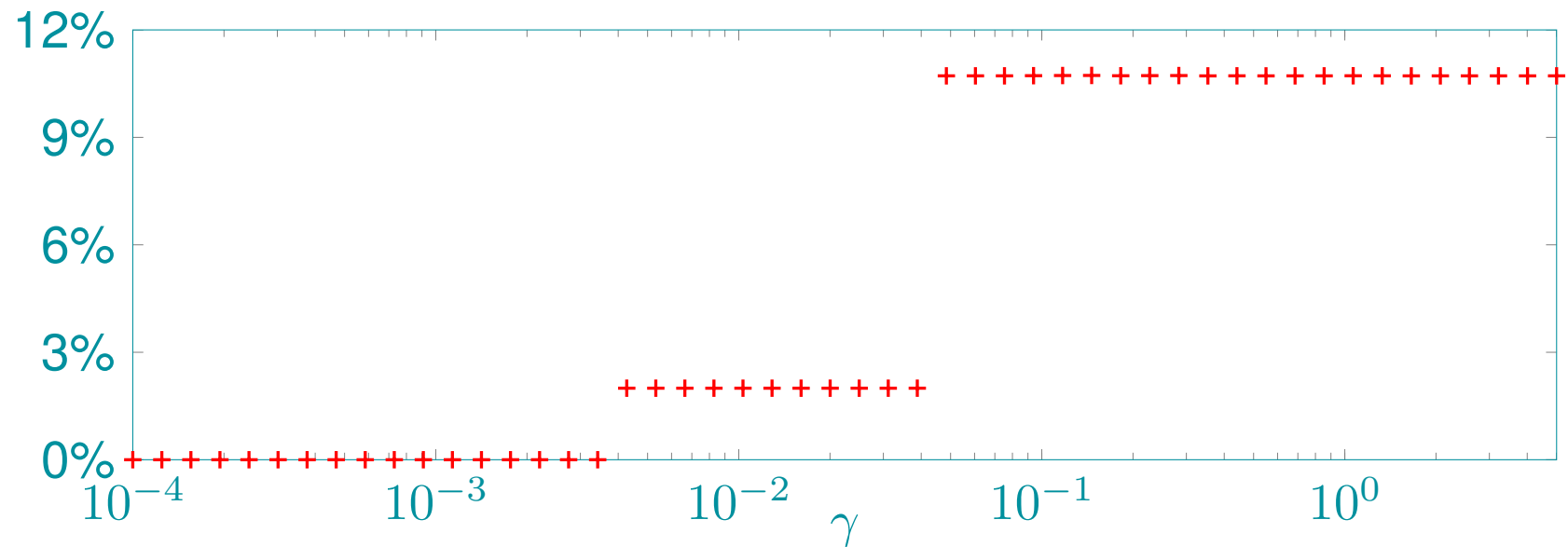
- CENTRALIZED GAIN

$$F_c = \begin{bmatrix} 0.3838 & 0.1961 & 0.1120 & 0.1120 & 0.1961 \\ 0.1961 & 0.3838 & 0.1961 & 0.1120 & 0.1120 \\ 0.1120 & 0.1961 & 0.3838 & 0.1961 & 0.1120 \\ 0.1120 & 0.1120 & 0.1961 & 0.3838 & 0.1961 \\ 0.1961 & 0.1120 & 0.1120 & 0.1961 & 0.3838 \end{bmatrix}$$

# Sparse and centralized controllers comparison

- PERFORMANCE DEGRADATION

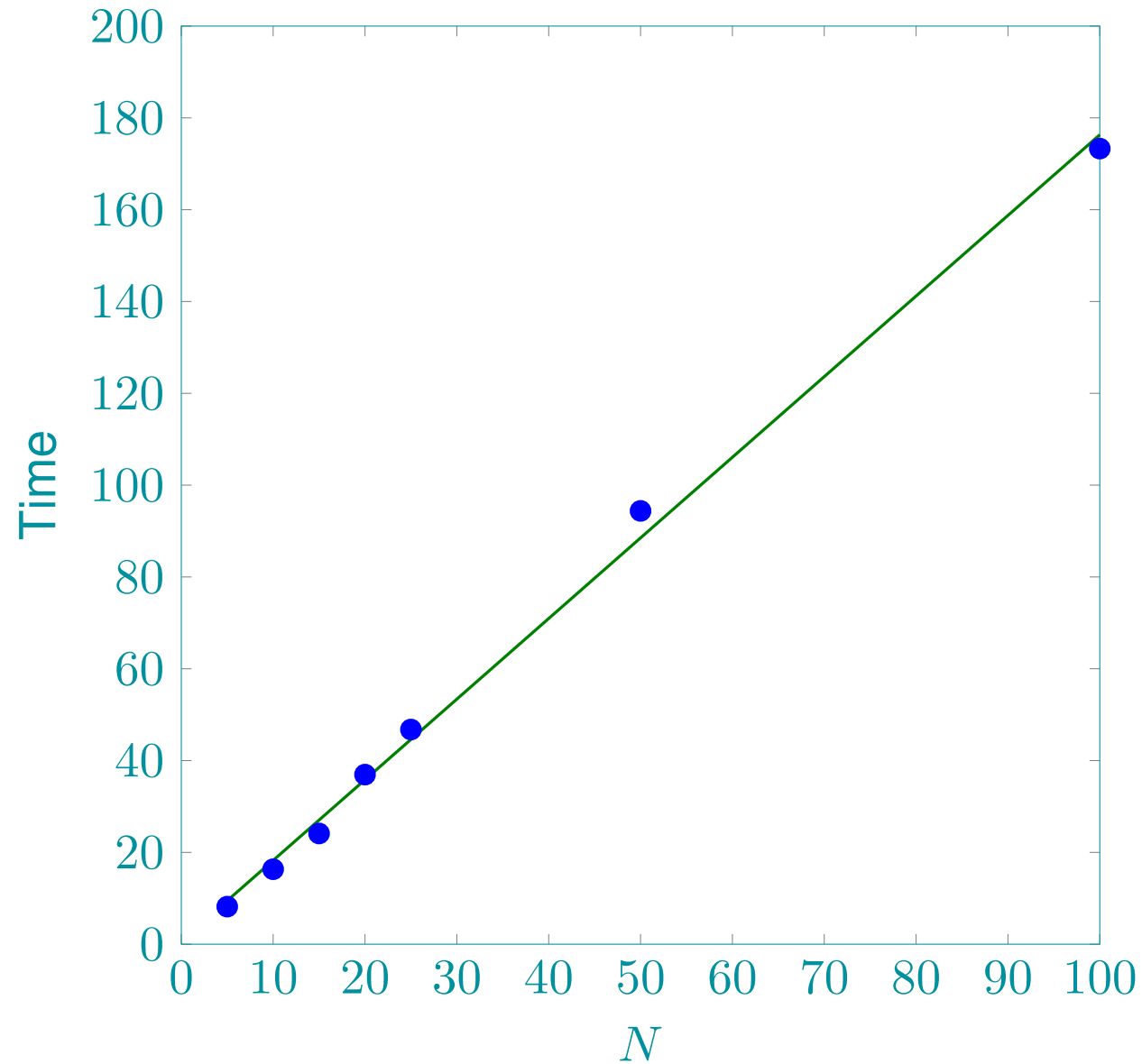
$$(J(F) - J(F_c)) / J(F_c)$$





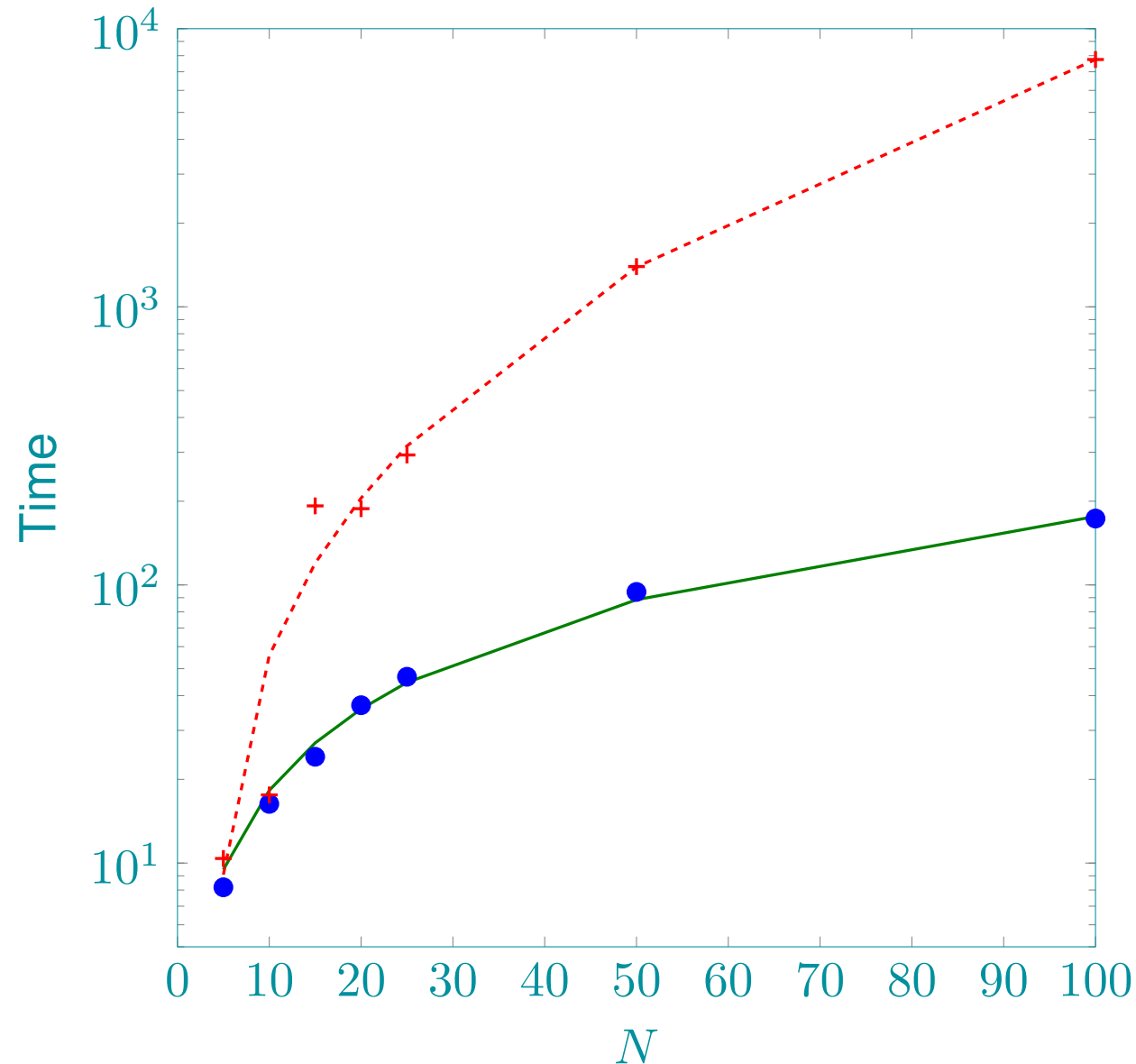
# Computational complexity

- LINEAR SCALING IN THE NUMBER OF SUBSYSTEMS  $N$



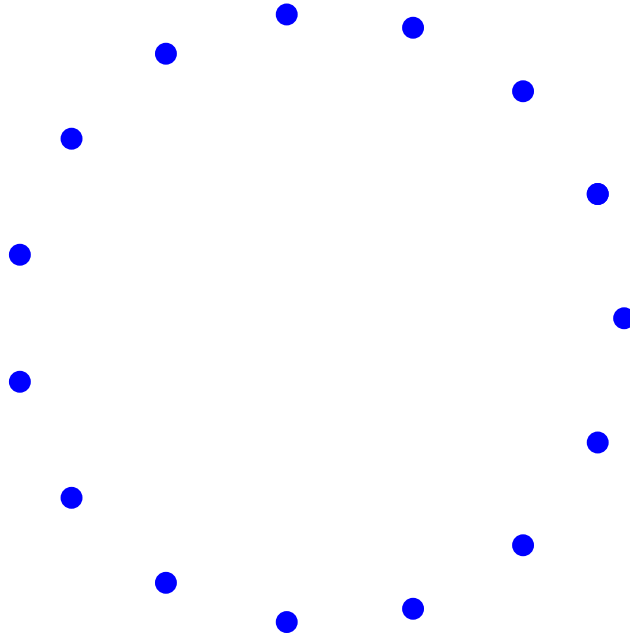
# Computational Complexity

- ALGORITHM (●) EXPLOITS VS. (+) DOES NOT EXPLOIT CIRCULANT STRUCTURE
- ★ (●) linear vs. (+) cubic scaling in the number of subsystems



# Distributed system with $N = 15$ subsystems

★ EVENLY DISTRIBUTED ON A CIRCLE

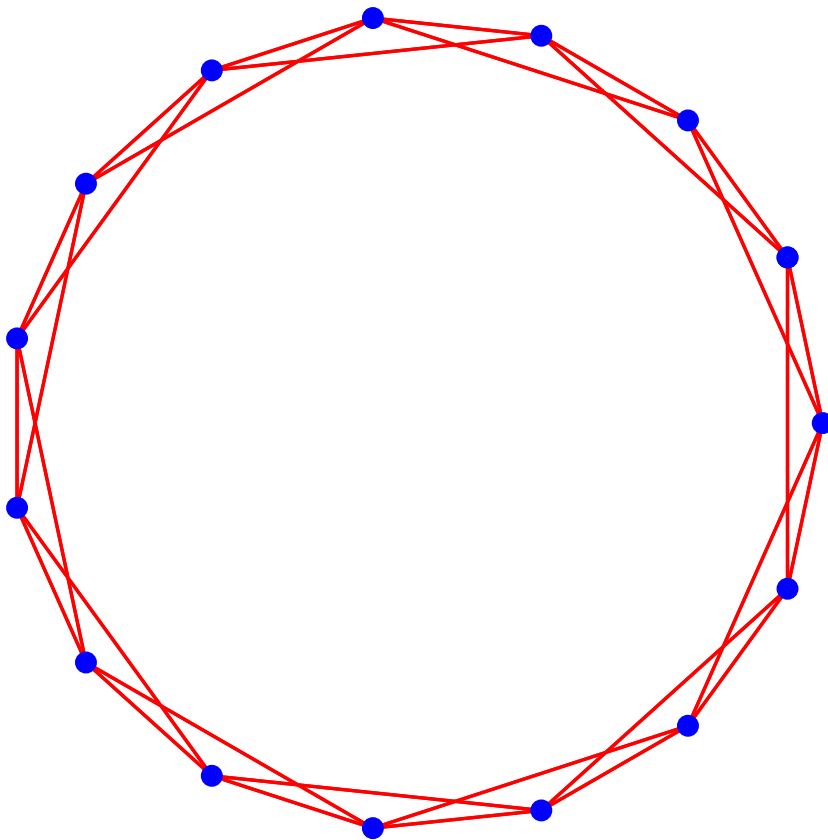


$$\begin{bmatrix} \dot{p}_i \\ \dot{v}_i \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} p_i \\ v_i \end{bmatrix} + \sum_{j \neq i} e^{\alpha(i,j)} \begin{bmatrix} p_j \\ v_j \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} (d_i + u_i)$$

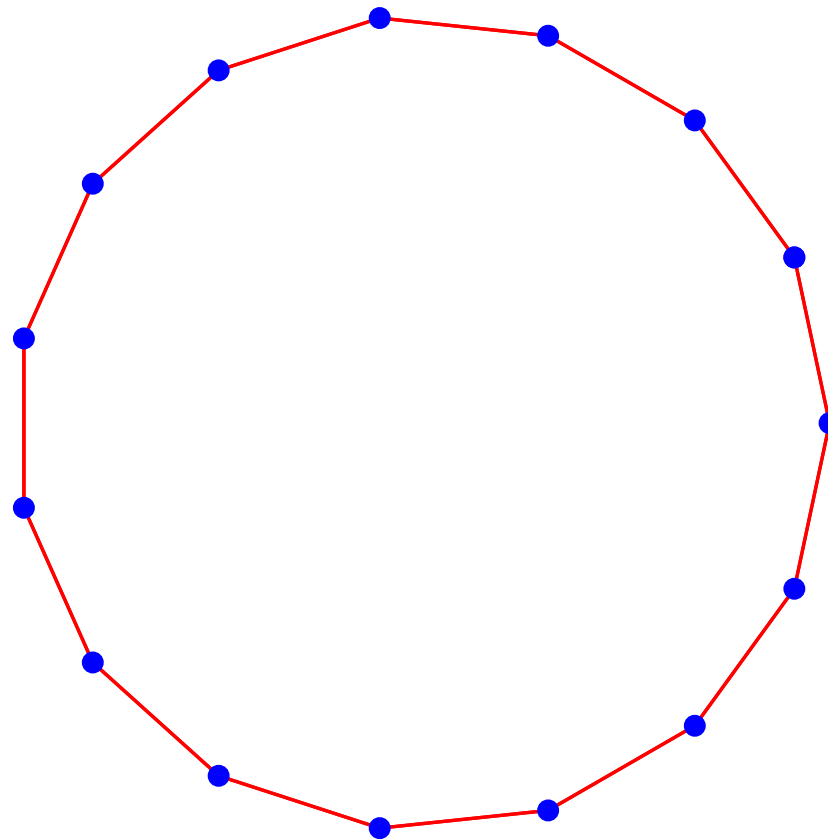
★  $\alpha(i, j)$ : EUCLIDEAN DISTANCE BETWEEN SUBSYSTEMS  $i$  AND  $j$

# Identified communication graphs

$$\gamma = 0.1389$$

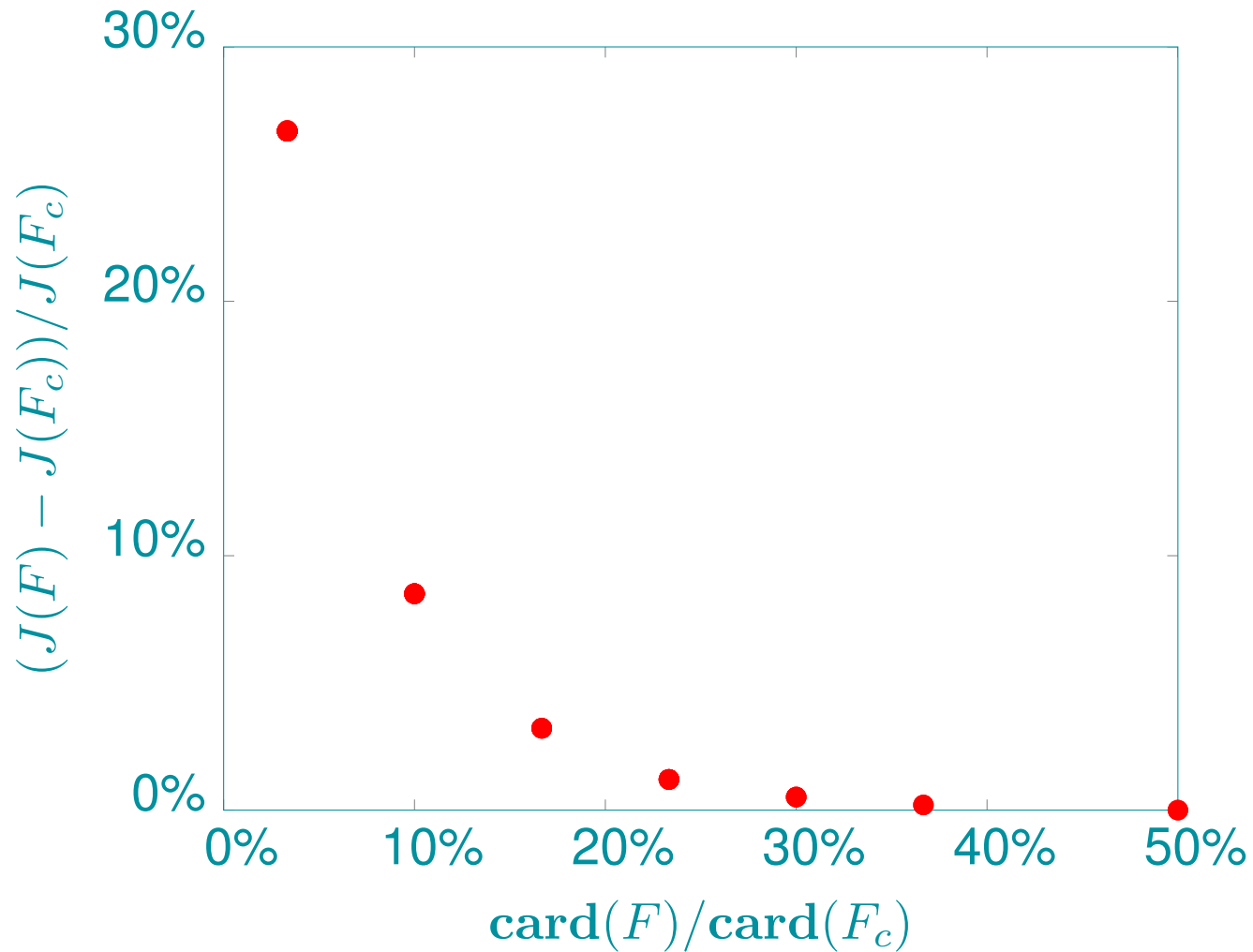


$$\gamma = 0.9103$$



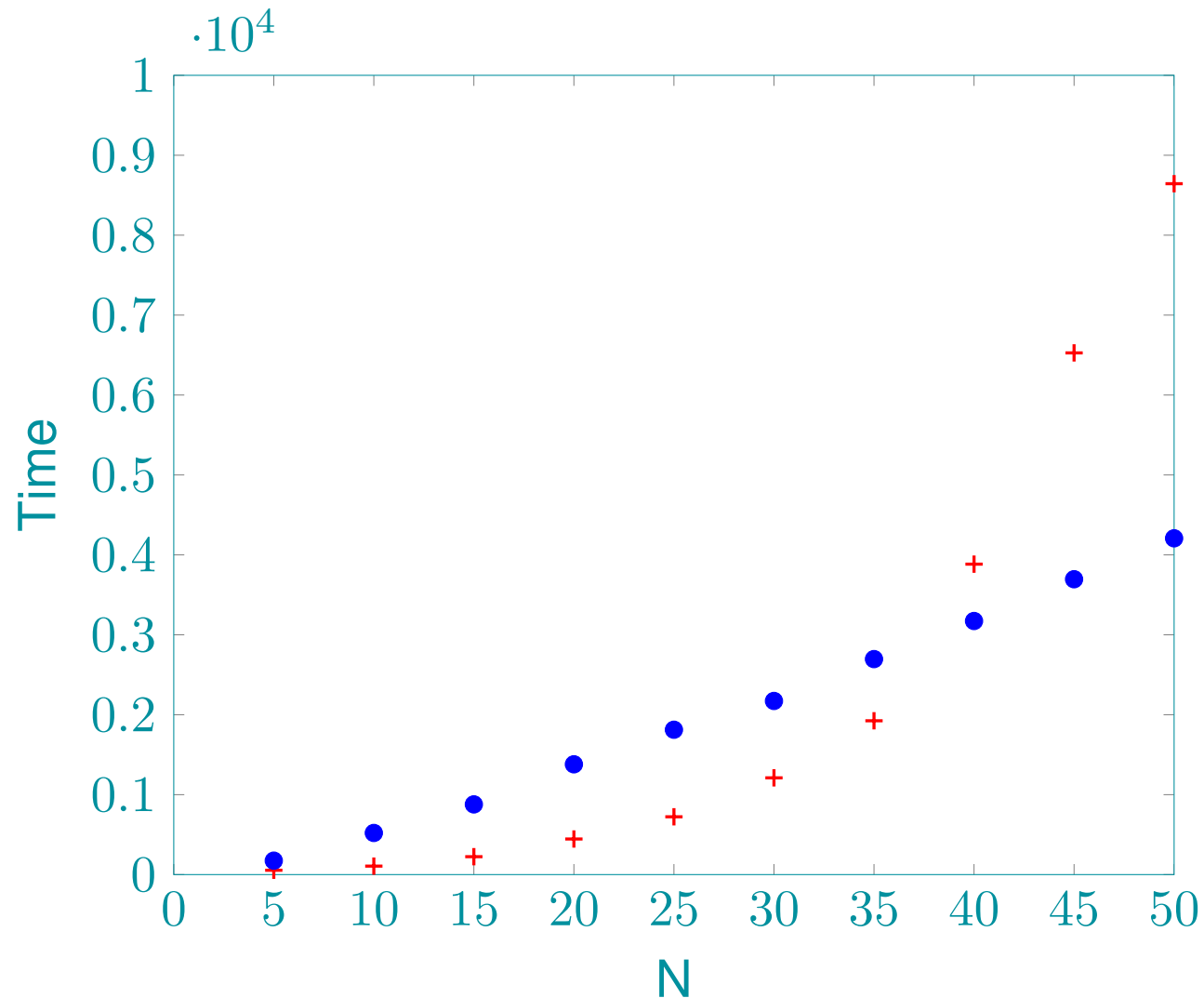
# Sparsity vs. Performance Degradation

- COMPARED TO CENTRALIZED CONTROLLER



# Computational Complexity

- ALGORITHM (●) EXPLOITS VS. (+) DOES NOT EXPLOIT CIRCULANT STRUCTURE
- ★ (●) linear vs. (+) cubic scaling in the number of subsystems



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## TEAM:



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