

# Computing over Unreliable Communication Networks

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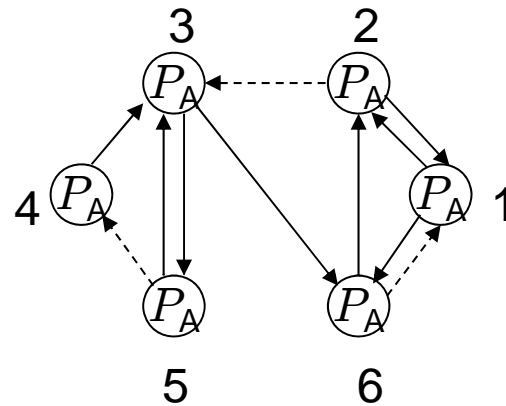
Iowa State University

Acknowledgments to: NSF

# Interconnected systems

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- ▶ Materials
- ▶ System Biology
- ▶ Computers networks
- ▶ Power grid
- ▶ Avionics systems
- ▶ Economics & Finance
- ▶ Ecology
- ▶ Traffic
- ▶ Social Networks
- ▶ Multi-agents systems



- ▶ Large dimensions
- ▶ Many nonlinearities
- ▶ ***Uncertainty in the interactions***
- ▶ ***Lots of feedback loops***
- ▶ Not clear separations

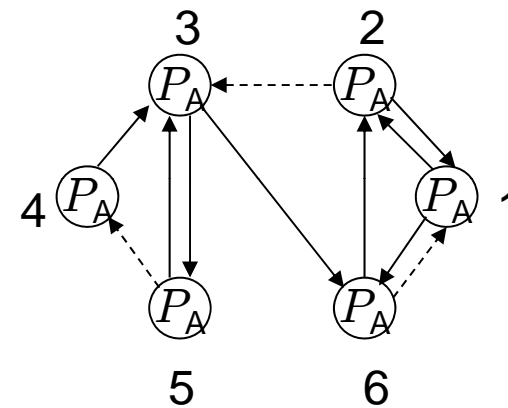
- ▶ Difficult to analyze/design, abrupt changes, complex unpredicted behaviors
- ▶ What are the determining factors?

# Interconnected systems: New opportunities

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New applications which are network distributed

- ▶ Estimation
- ▶ Detection
- ▶ Control
- ▶ Optimization
- ▶ Computation



New developments

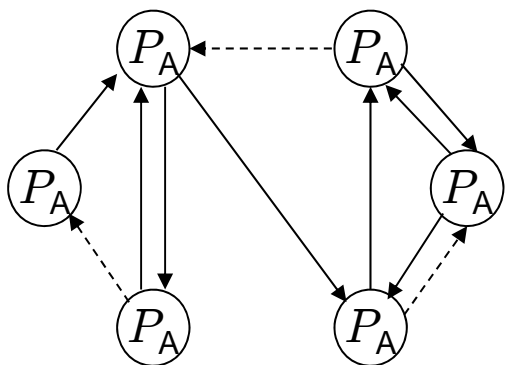
- ▶ Integrated theory of control and information
- ▶ Dynamical system view of distributed computing algorithms

Focus on multi-agent systems with “simple” agents

# Channels in the Loops

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- ▶ How do communication channels affect networked systems?
- ▶ Concentrate on channel “fading” and additive noise

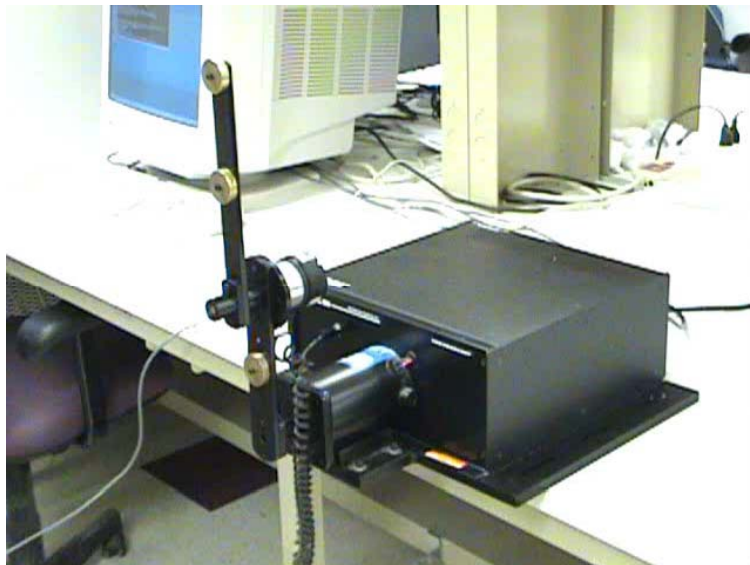
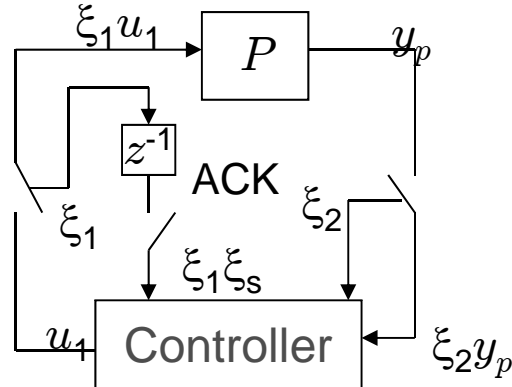


- ▶ ***Uncertainty in the interactions***
- ▶ ***Lots of feedback loops***

# Protocol Design

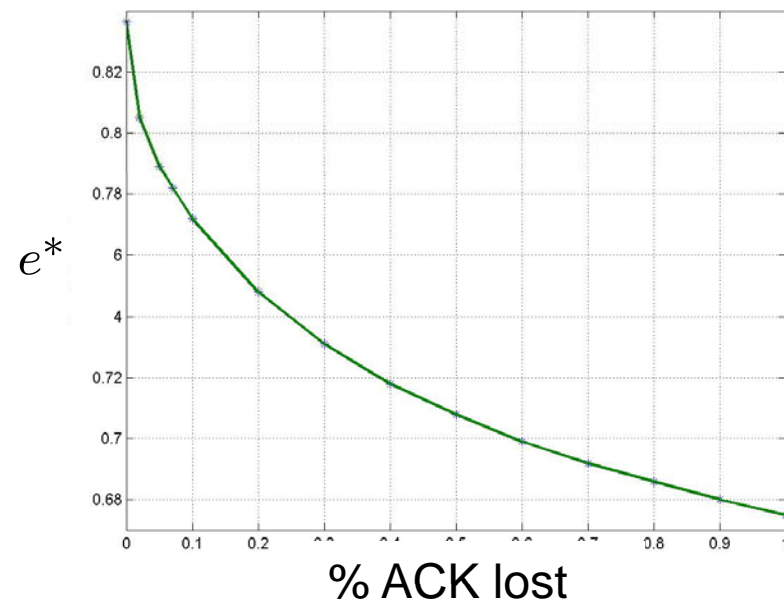
(Elia, Eisenbeis TAC11, Padmasola Elia 06)

- ▶ New protocols need to focus on **data freshness** rather than **data integrity**



Actuator-Sensor 70% packet drop, Service channel 50% ACK losses

QoS for MS stability



QoS

# Outline

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- ▶ Unreliable Networks (Fading Network Framework)
- ▶ Networked control approach to distributed computation of averages
  - ▶ Limitations due to unreliable communication
  - ▶ Emergence of complex behavior
  - ▶ Mitigation techniques
- ▶ New perspective on distributed optimization systems
  - ▶ Distributed optimization over unreliable networks

# Fading Channels as Uncertain Systems

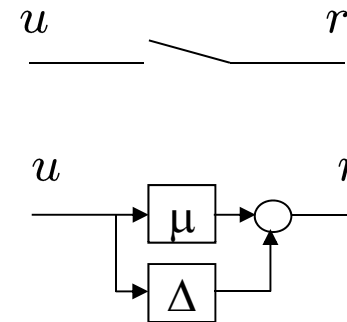
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Intermittent channel with probability  $\epsilon$

$$r(k) = \xi(k)u(k)$$

$\xi(k) \sim$  Bernoulli, IID

$$\mu \triangleq \mathbf{E}\{\xi(k)\}, \quad \bar{\sigma}^2 \triangleq \mathbf{E}\{(\xi(k) - \mu)^2\}$$



Re-parametrization(s)

$$r(k) = (\mu + \Delta(k))u(k), \quad \mathbf{E}\{\Delta(k)\} = 0; \quad \text{var}\{\Delta(k)\} = \sigma^2 = \bar{\sigma}^2$$

$$r(k) = \mu(1 + \Delta(k))u(k), \quad \mathbf{E}\{\Delta(k)\} = 0, \quad \text{var}\{\Delta(k)\} = \sigma^2 = \frac{\bar{\sigma}^2}{\mu^2}$$

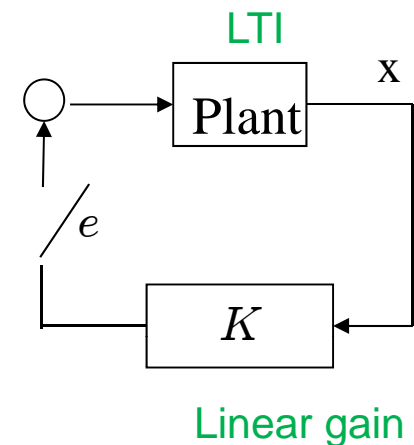
- ▶ Model for packet loss in networks (concentrate on fading neglect quantization)
- ▶ Special case of analog memory-less multiplicative channel
- ▶ Extends to Gaussian fading channels  $\xi(k) \sim N(1, \sigma^2)$  also with memory

# A Simple Problem

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$x(k)$  state (r.v.) of the system at time  $k$

$$Q(k) = E \{ x(k)x(k)' \}$$



## Mean Square Stability

$\lim_{k \rightarrow \infty} Q(k) \rightarrow \mathbf{0}$  for any initial  $Q_0 = Q(0) \geq 0$       Noiseless

$\lim_{k \rightarrow \infty} Q(k) \rightarrow Q$  for any initial  $Q_0 = Q(0) \geq 0$       With white-noise input

Minimal Channel Quality for Mean Square Stability?



# A general framework: the Fading Network (Elia 05)

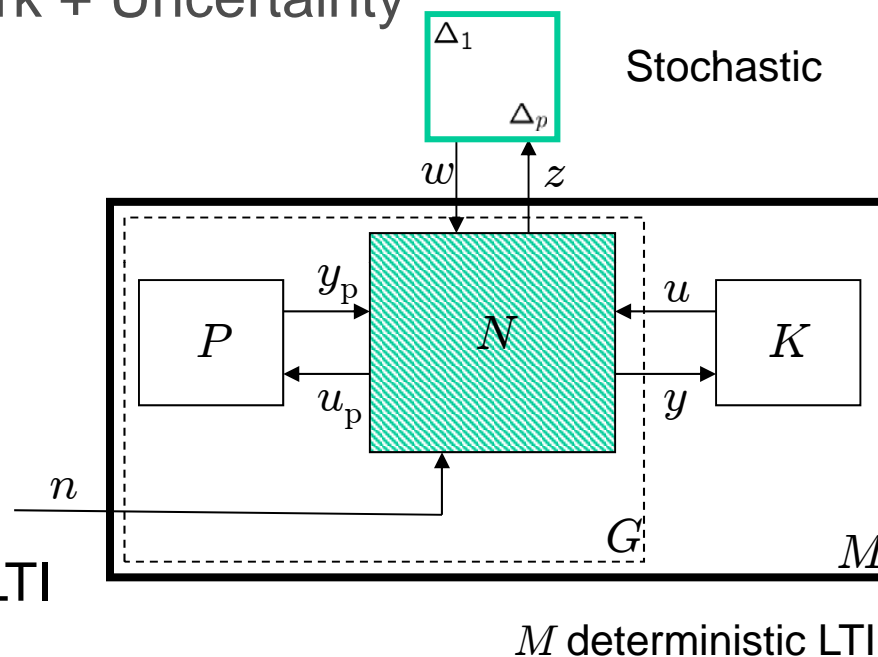
Fading Network = Mean Network + Uncertainty

- Uncertainty is Stochastic

$\Delta_i(k)$  IID in  $k$ , Independent in  $i$   
Zero Mean, var =  $\sigma^2$

$$\|\Delta\| = \sigma^2$$

- Mean Network,  $N$ , deterministic LTI



MS Stability margin

$$\mu_{MS}(M, \Delta) = \frac{1}{\{\sup \sigma^2 : \text{the closed loop system is MS stable}\}}$$

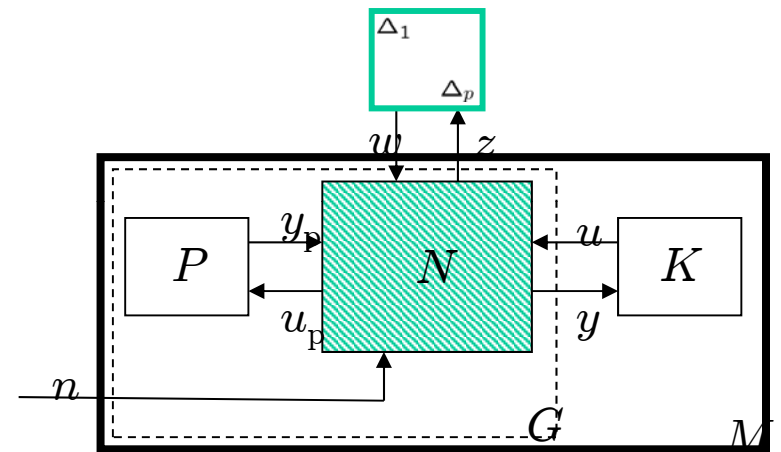
# MS Stability Robustness Analysis (Eliä 05)

Given  $M = \begin{array}{c|c} \mathcal{A} & \mathcal{B} \\ \hline \mathcal{C} & \mathcal{D} \end{array}$  stable with  $\mathcal{D}$  strictly upper/lower triangular

$$\text{Let } \hat{M} = \begin{pmatrix} \|M_{11}\|_2^2 & \dots & \|M_{1p}\|_2^2 \\ \vdots & \dots & \vdots \\ \|M_{p1}\|_2^2 & \dots & \|M_{pp}\|_2^2 \end{pmatrix}$$

$$\text{Then } \mu_{MS} = \frac{1}{\rho(\hat{M})}$$

$\rho(\cdot)$  = spectral radius



CL system MS stable iff  $\sigma^2 \rho(\hat{M}) < 1$

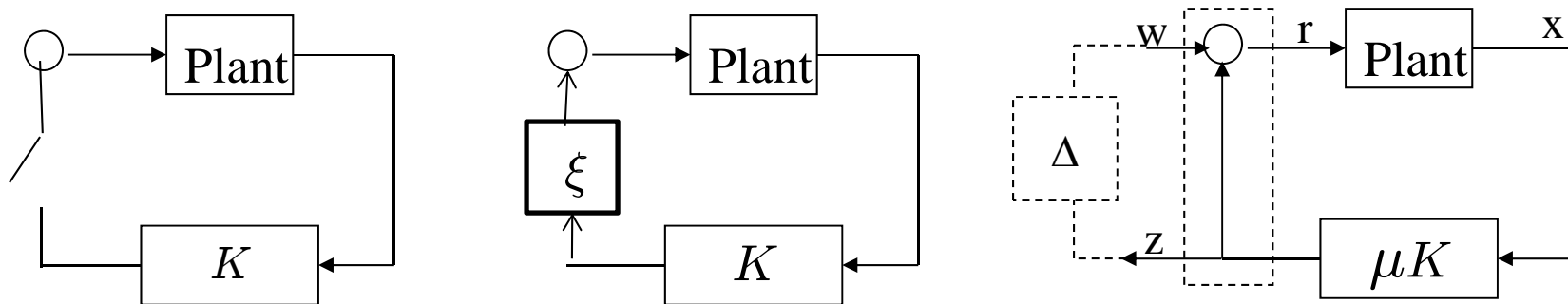
Separation result

Based on ElGaoui 95, Ku Athans 77, Willems Blankenship 71, Kleinman 69 Wonham 67.  
Related to El Bouhtouri et all 02, Jianbo Lu Skelton 02.

# State-Feedback with One Channel

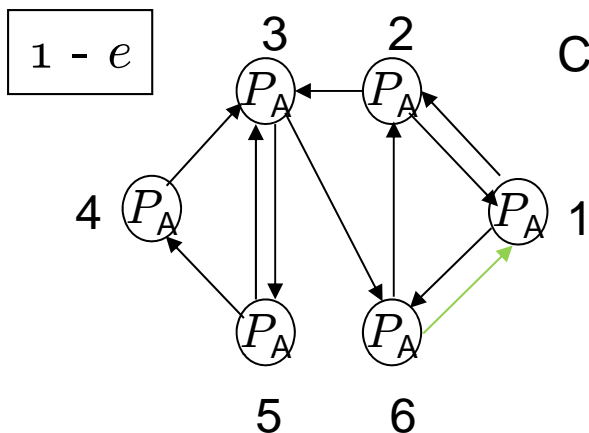
State feedback with one memoryless multiplicative channel at the plant input

$$\xi(k) = \mu(1 + \Delta(k))$$



- For the intermittent channel:  $\frac{e}{1-e} \|M\|_2^2 < 1 \Rightarrow e < \frac{1}{\prod_i |\lambda_i^u(A)|^2} = e^*$

# Why is single loop stabilization relevant?



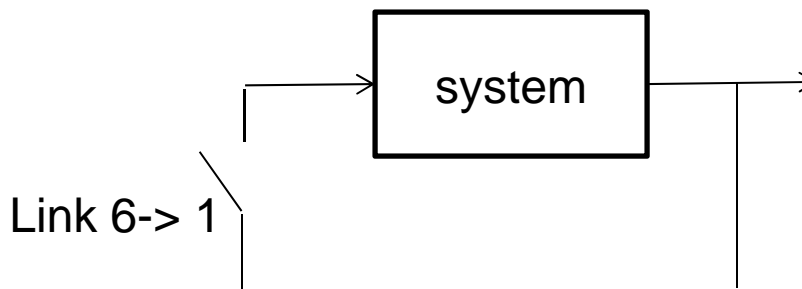
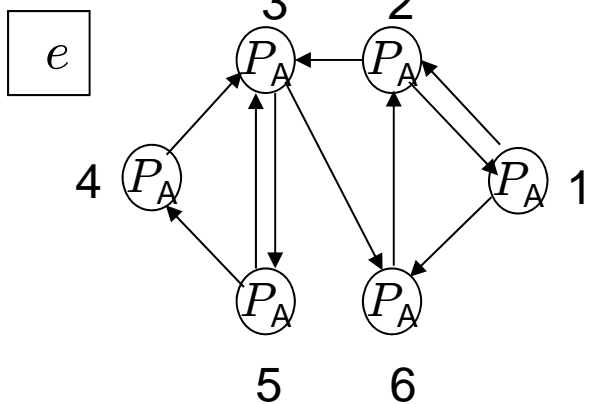
Collection of interconnected stable system can be unstable

$$P_A : y_p = \frac{0.5}{z(z-1)} u_p$$

$$u_{pi} = n_i + \frac{1}{|N_i|} \sum_{j \in N_i} (y_{pj} - y_{pi}),$$

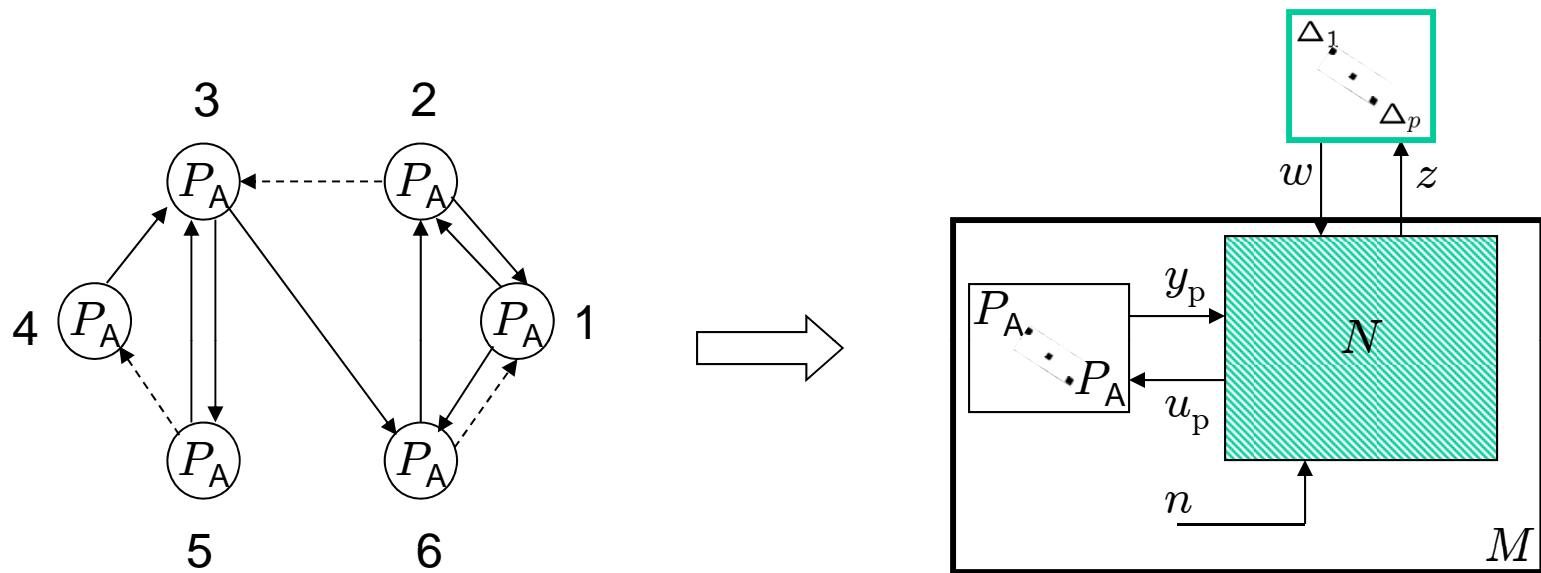
System

- Stable if link 6-1 is **present**
- Unstable if link 6-1 is **absent**
- Mean Stable is  $e < 0.517$
- Mean Square stable if  $e < 0.501$



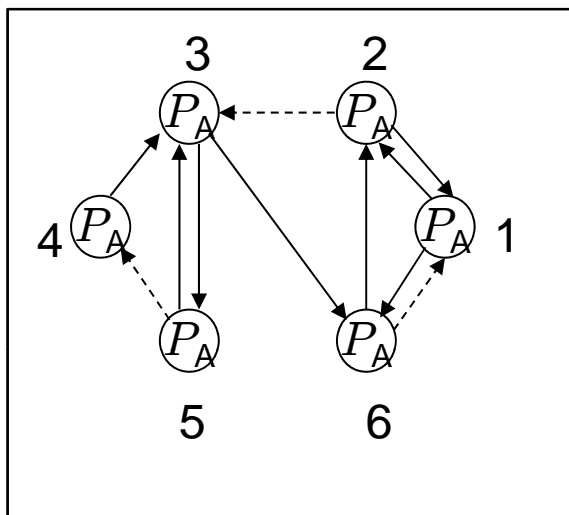
Similar to one fading channel in the loop

# Limitations for Multi-agent Systems.



- ▶ Many channels in many loops
- ▶ Same tool applies
- ▶ QoS analysis more complex
- ▶ Simple mechanism for emergence of complex behavior

# Consensus: a paradigm for distributed computation

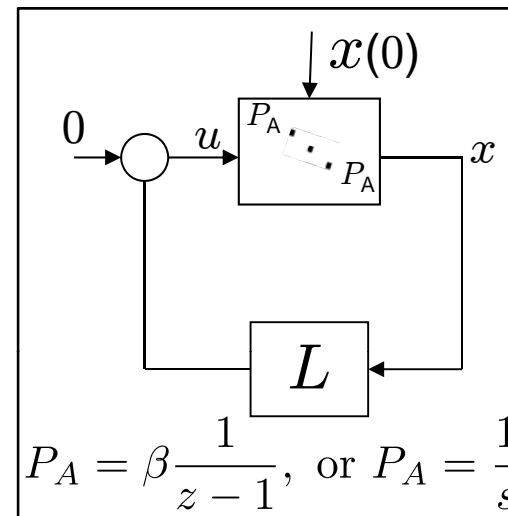


Discrete-time

$$x_i^+ = x_i + \beta \sum_{j \in N_i} a_{ij} (x_j - x_i)$$

Continuous-time

$$\dot{x}_i = \sum_{j \in N_i} a_{ij} (x_j - x_i)$$



All the nodes are the same.

Each node use the relative error from its neighbors to update its own state.

The neighbors are determined by a graph.

Under certain conditions

$$\lim_{t \rightarrow \infty} x_i(t) = \frac{1}{n} \mathbf{1}^T x(0)$$

Tsitsiklis, Olfati-Saber, Scutari, Fax, Murray, Zampieri, Fagnani, Cortes, Pesenti, Giuliatti, Ren, Beard, Papachristodoulou, Lee, Jadbabaie, Low,....

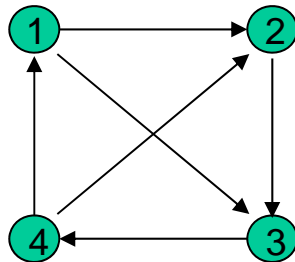
# Basic Graph Theory

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- ▶ (**Laplacian Matrix**) We can associate each edge  $(i, j)$  with a positive weight  $a_{ij}$ , the Laplacian matrix  $L = [l_{ij}]$  is defined as

$$l_{ij} := \begin{cases} \sum_{j \in N_i} a_{ij} & \text{if } j = i \\ -a_{ij} & \text{if } j \neq i \end{cases}$$

- ▶ Example: For 0-1 weights



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

- ▶  $L\mathbf{1} = 0$
- ▶ The left eigenvector of  $L$  associated with **zero eigenvalue** is all positive if the graph is **strongly connected**
- ▶ (**Balanced Laplacian**) satisfy  $\sum_j a_{ij} = \sum_j a_{ji}, \forall i$ , needed for averaging

# Limitations on Information Exchange

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Averaging over unreliable channels + noise ?

$$x_i(k+1) = x_i(k) + \beta \sum_{j \in N_i} \xi_{ij}(k) [x_j(k) - x_i(k)] + v_i(k)$$

$\beta$  update gain  $\geq 0$

$\xi_{ij}$  packet drop  $ij$  channel  $\Pr(\xi_{ij}(k) = 1) = \mu_{ij} = \text{QoS}$

$v_i$  total additive noise to node  $i$ ;  $N(0,1)$

The model describes very simple-minded interacting agents

Assume  $\mu_{ij} = \mu$  for simplicity



# Fading Network and system decomposition

$$x_i(k+1) = x_i(k) + \beta \sum_{j \in N_i} \xi_{ij}(k) [x_j(k) - x_i(k)] + v_i(k)$$

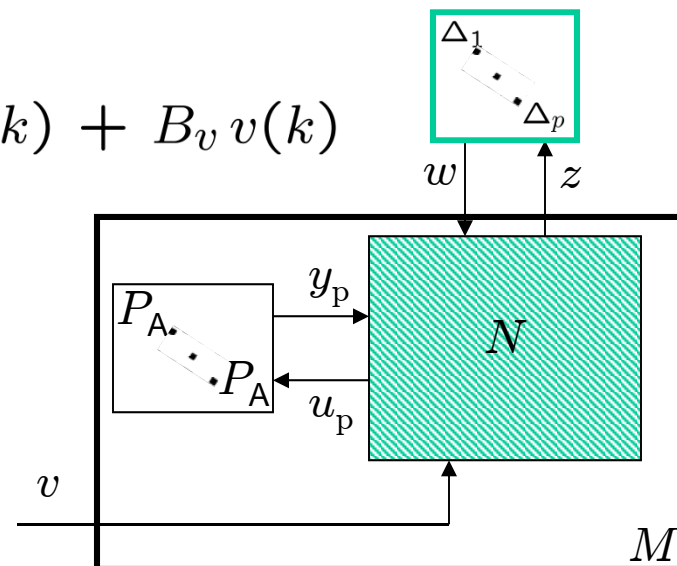
- Uncertainty re-parametrization

$$\xi_{ij} = \Delta_{ij} + \mu \quad \mathbf{E}(\Delta_{ij}) = 0 \quad \text{Var}(\Delta_{ij}) = \sigma^2 = \mu(1 - \mu)$$

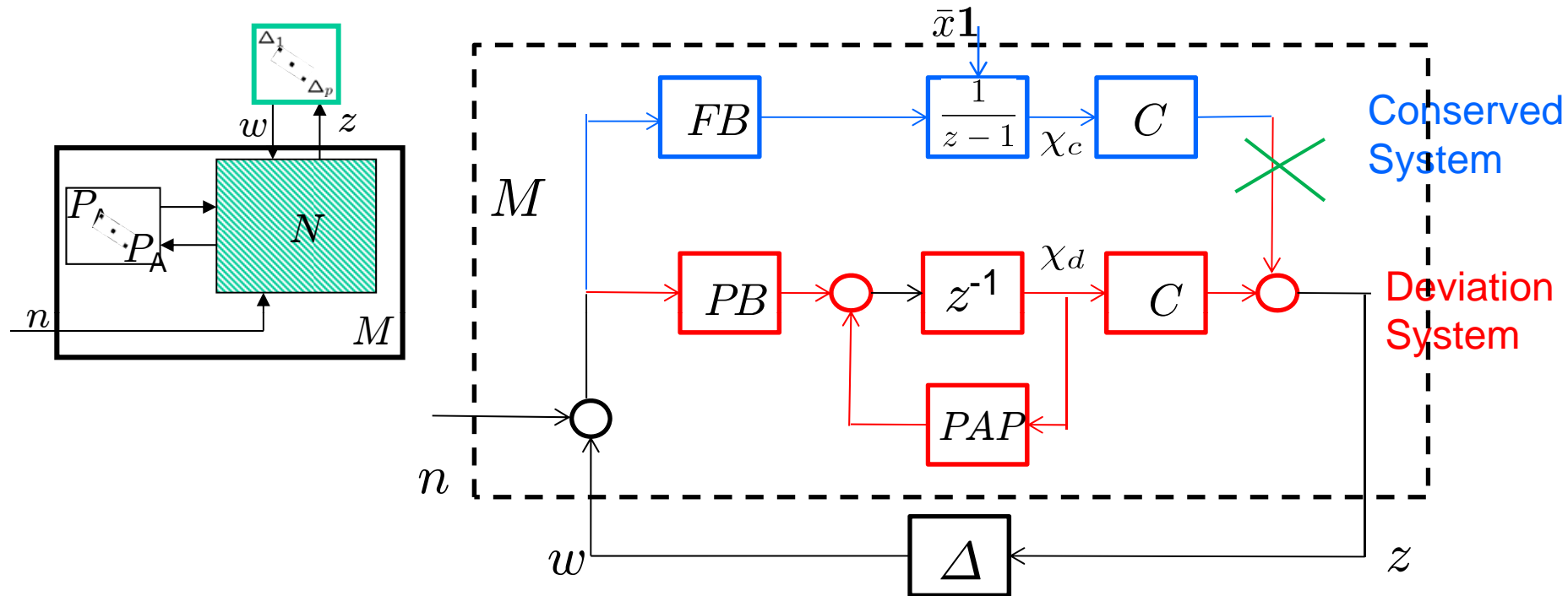
- State-space Equations for  $(M, \Delta)$

$$\chi(k+1) = A \chi(k) + B \Delta(k) C \chi(k) + B_v v(k)$$

- $M=(A,B,C)$  has special structure



# System Decomposition: Block Diagram

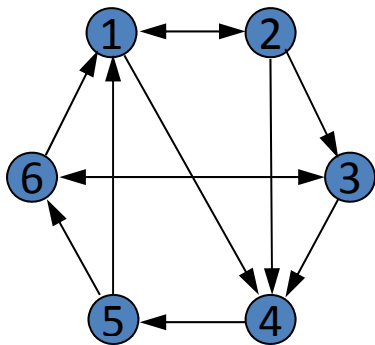


**Decomposition:** Conserved + Deviation state  $\chi = \chi_c + \chi_d$

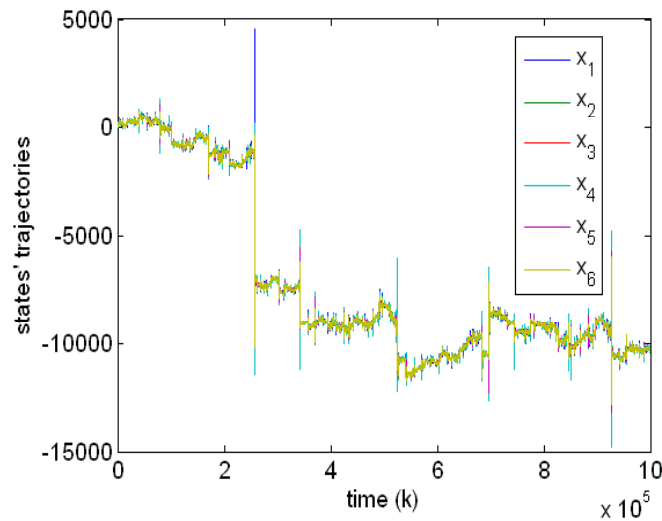
$$\chi_c = \frac{1}{n} \mathbf{1}^T \chi, \quad \chi_d = \left(1 - \frac{1}{n} \mathbf{1}^T\right) \chi$$

When there is no noise or fading,  $\chi_c$  is the consensus value,  $\chi_d$  goes to zero

# Emergence of new collective complex behavior

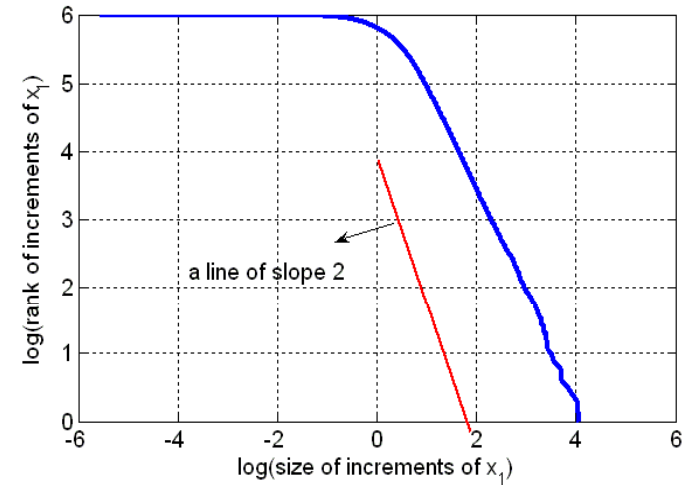


$$\beta = 0.822$$
$$e = 0.5, \tau = 5$$
$$\sigma_v^2 = 0.04$$



Agents' states

[Wang Elia MTNS10, TAC12]



Loglog plot of the increments of  $x_1$

- ▶ Moment instability leads to power laws behaviors (under suitable assumptions)
- ▶  $\chi_c$  Integration of process with unbounded second moment (Levi's processes)

# Emergence of new collective complex behavior

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For directed IID switching and strongly connected mean graph,  
assume the deviation system converges to an invariant distribution  
driven by Gaussian noise.

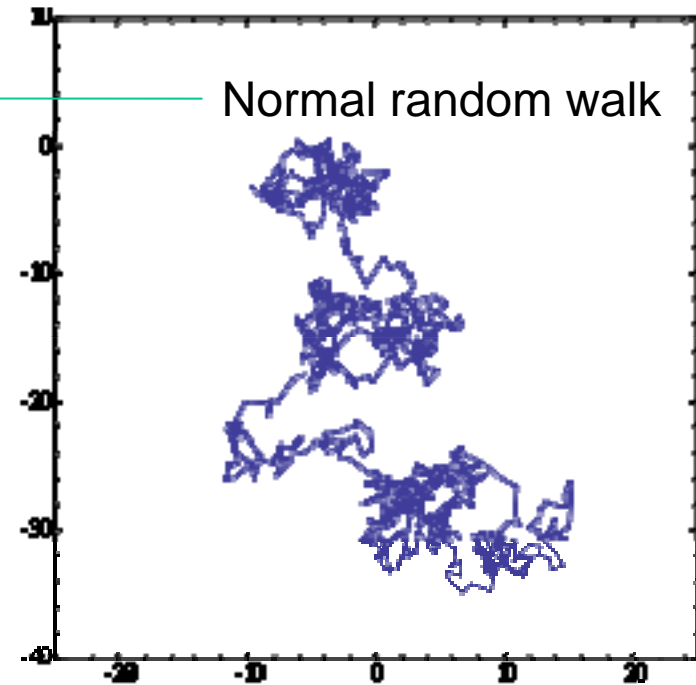
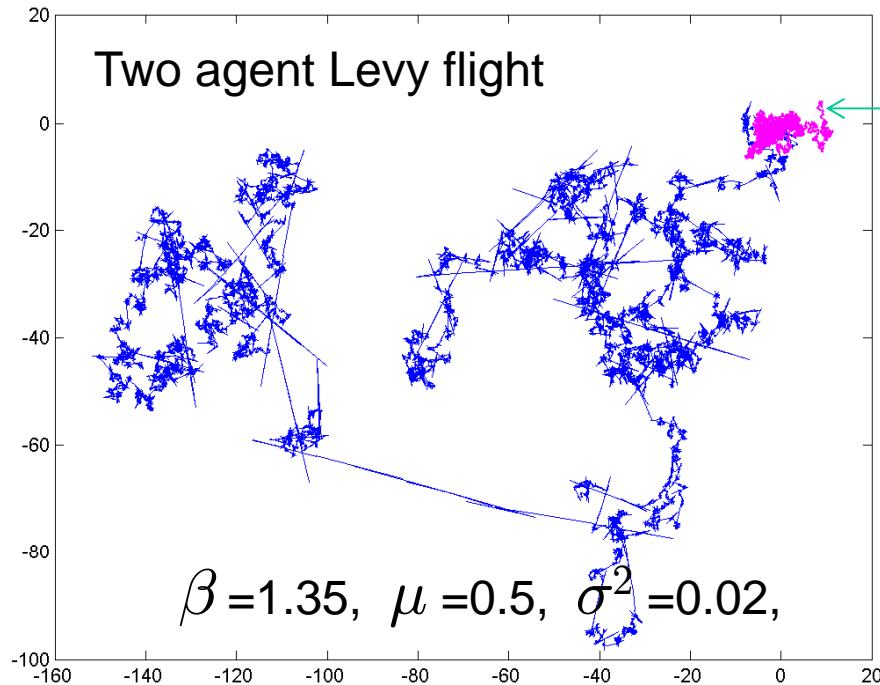
$\chi_c$  is a hyper-jump-diffusion  $\lim_{k \rightarrow \infty} \{\chi_c(k) - \chi_c(k-1)\} \stackrel{dis}{=} R, \quad \mathbf{E}\{RR'\} = \infty$



Deviation system is Mean Square unstable

- ▶  $\chi_c$  is a Levy flight,  $\lim_{t \rightarrow \infty} t^\alpha \Pr(|R| > t) > 0, 0 < \alpha \leq 2$   
for a two-node system ([Kesten])
- ▶ Emergent complex behavior is global (collective)
- ▶ Long range impact of local criticality.

# Levy flights vs. Normal random walk



- ▶ In the distribution of human travel [Brockmann]
- ▶ In economics and financial series [Mandelbrot, Sornette, Mantegna]
- ▶ In foraging search patterns of several species [Raynolds, Bartumeus]
- ▶ **Exploitation** cooperative searches and optimization?
- ▶ **Mitigation** strategies ?

# MS Stable Consensus with Channel Noise

$n=10$

$d=4$

$\beta=0.2$

$e=0.9$

Noise var.  $1e-6$



# MS Unstable Consensus no Noise

$n=10$

$d=4$

$\beta=0.9$

$e=0.9$

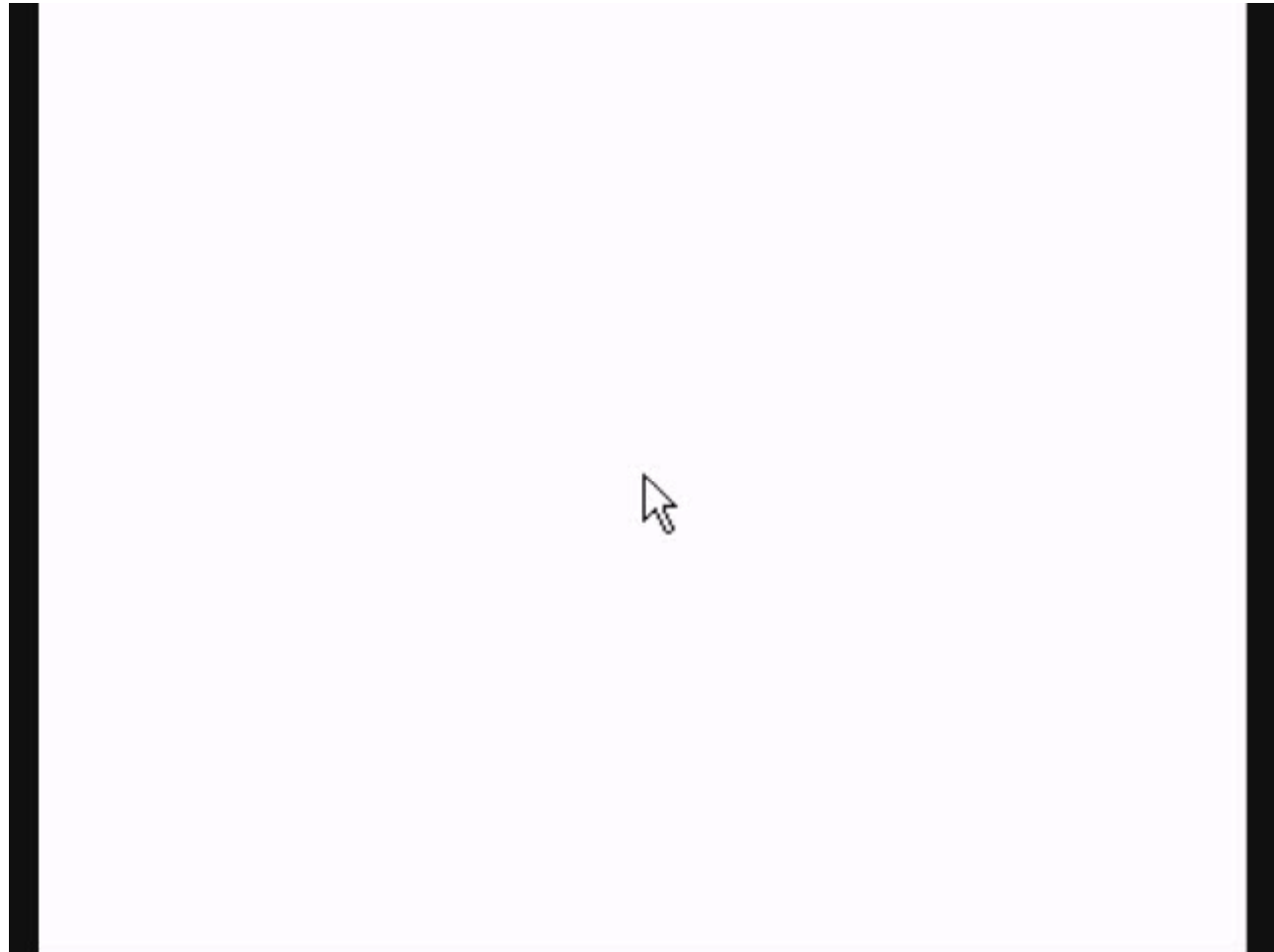
Noise var.=0



# MS Unstable Consensus with Channel Noise

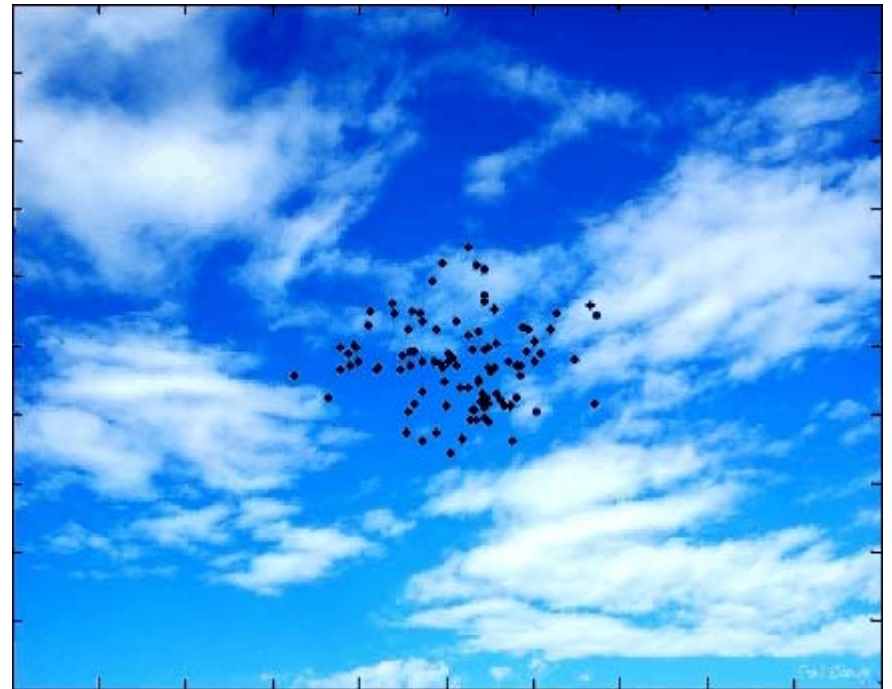
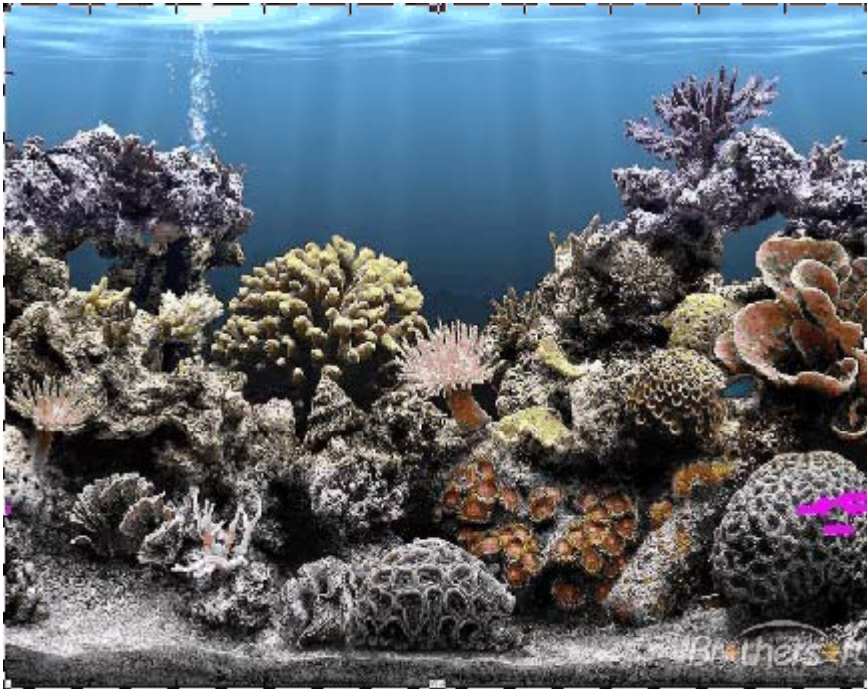
Emergence of complex behavior

- 10 nodes
- 4 neighbhds
- $\beta=0.9$
- $e=0.9$
- Noise var.  $1e-6$





# Unreliable communication: a mechanism for emergent behavior



Constant speed, averaging directions

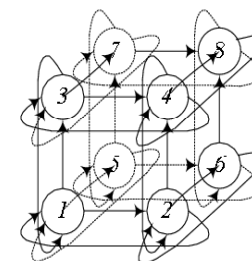
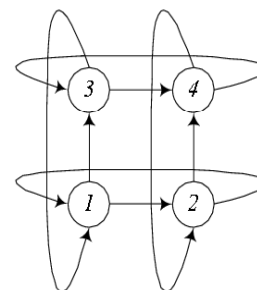
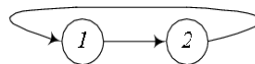
# A Mechanism for Complex Behavior

Power laws and Levy flights are endemic in complex systems

- ▶ Often believed due to high-dimensional nonlinear effects
- ▶ Presented a simple linear small dimensional LTI system that exhibits complex behavior.
- ▶ Overlooked mechanism: unreliable information exchange.

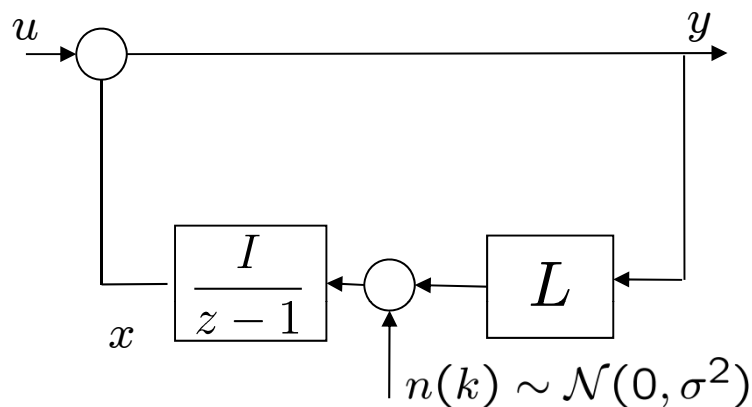
- ▶ Checking  $\rho \begin{pmatrix} \|M_{11}\|_2^2 & \dots & \|M_{1p}\|_2^2 \\ \vdots & \dots & \vdots \\ \|M_{p1}\|_2^2 & \dots & \|M_{pp}\|_2^2 \end{pmatrix}$  convex but cumbersome

- ▶ Robust organizational structures?



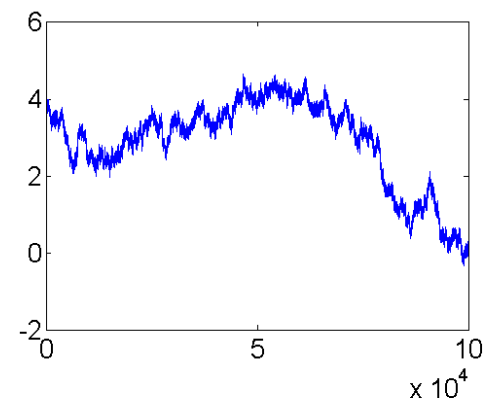
[Wang, Elia CDC08, Ma, Elia acc12]

# Fragility to additive noise



[Spanos at all]

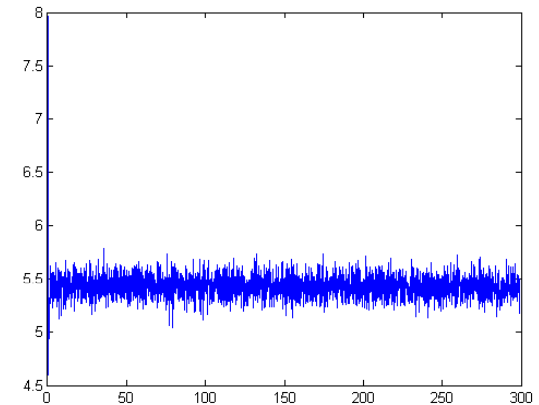
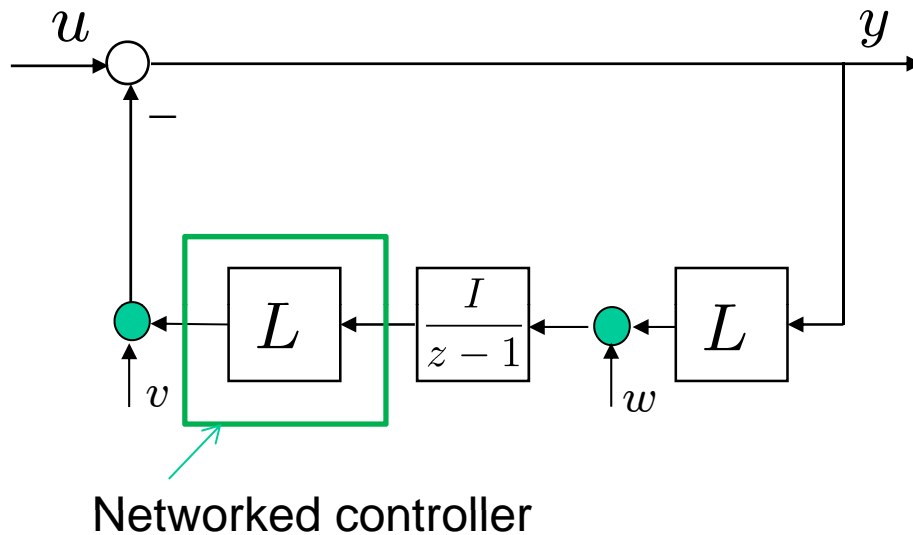
MIMO pole-zero cancellation



Output trajectories

- ▶ Variation due to [Spanos at all] allows inputs,  $y$  converges to average  $u$
- ▶ **Average value is lost:** (random walk) no useful for distributed computation
- ▶ State deviations are zero mean bounded variance
- ▶ Still OK for tracking/agreement (clock synchronization, load balancing,....)

# New algorithm resilient to noise



Output trajectories

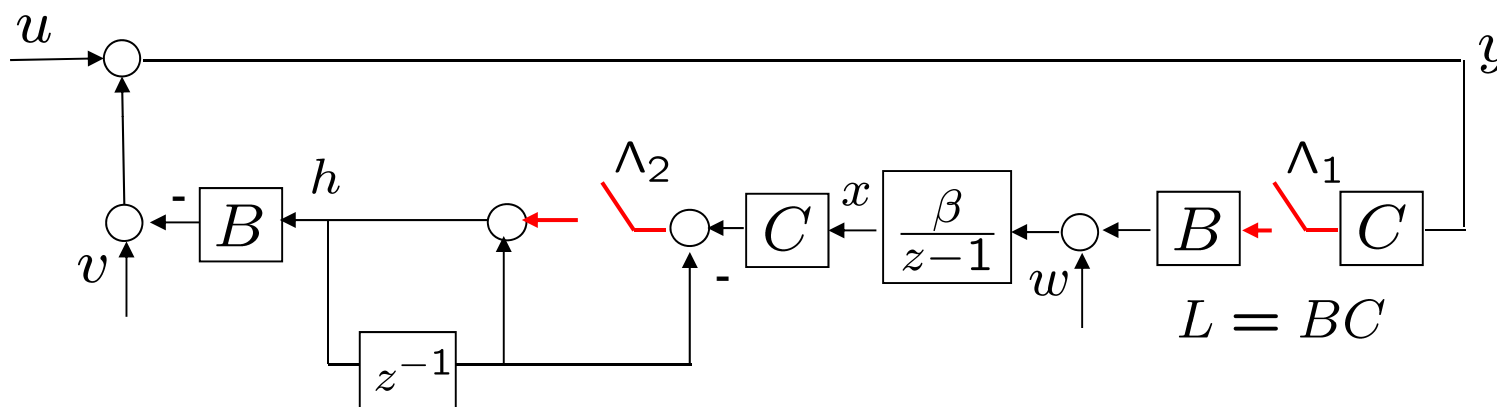
- ▶ Main idea: prevent random walk to show at the output
- ▶ Cost: communication and computation is doubled
- ▶ Problem: not all graph Laplacian can be used (Network controllers?)

$$w \sim \mathcal{N}(0, \Sigma_w) \quad v \sim \mathcal{N}(0, \Sigma_v)$$

# Resilience to channel intermittency

Need smarter agents:

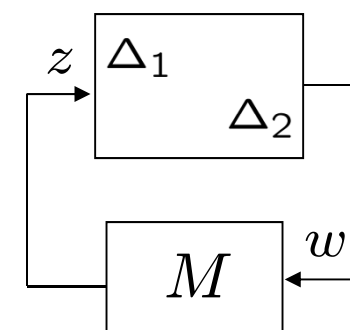
- ▶ know the state of the channels with their neighbors
- ▶ use channel state information (CSI)-- Hold last good message



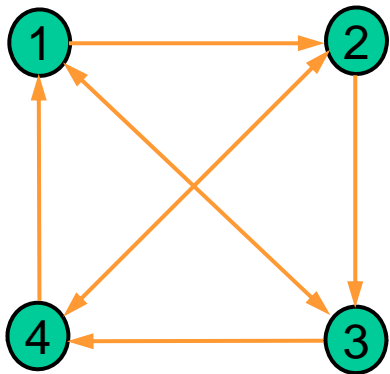
$$B = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix},$$

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

$$C = \begin{bmatrix} 1 & 0 & -1 & 0 \\ 1 & 0 & 0 & -1 \\ -1 & 1 & 0 & 0 \\ 0 & 1 & 0 & -1 \\ -1 & 0 & 1 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & -1 & 0 & 1 \\ 0 & 0 & -1 & 1 \end{bmatrix}.$$

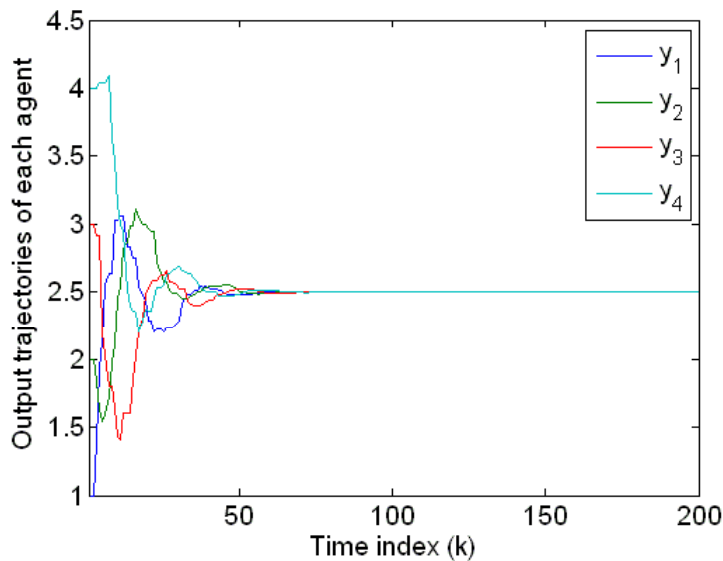


# Example: Average Robust to Switches and Noise

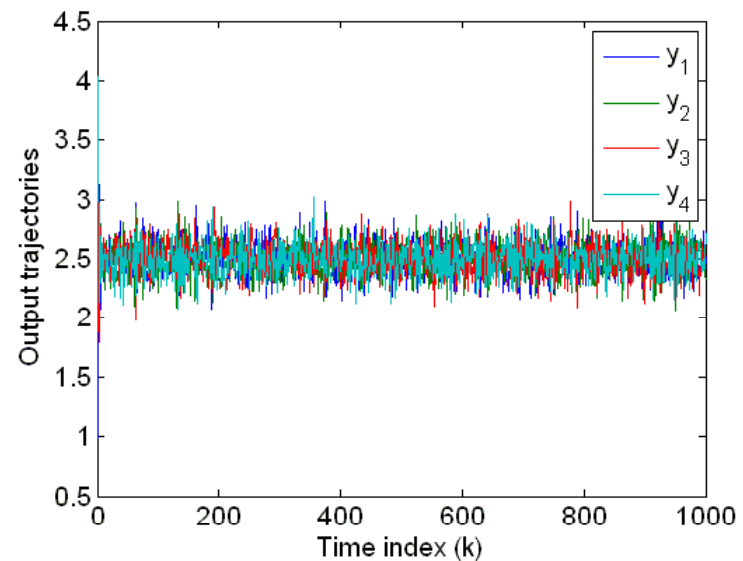


$$\beta = 0.04, \mu = 0.5$$
$$\sigma_{v_i}^2 = \sigma_{w_i}^2 = 0.04^2$$
$$u = [1 \ 2 \ 3 \ 4]'$$

Approximately correct analog computing



Switching topology

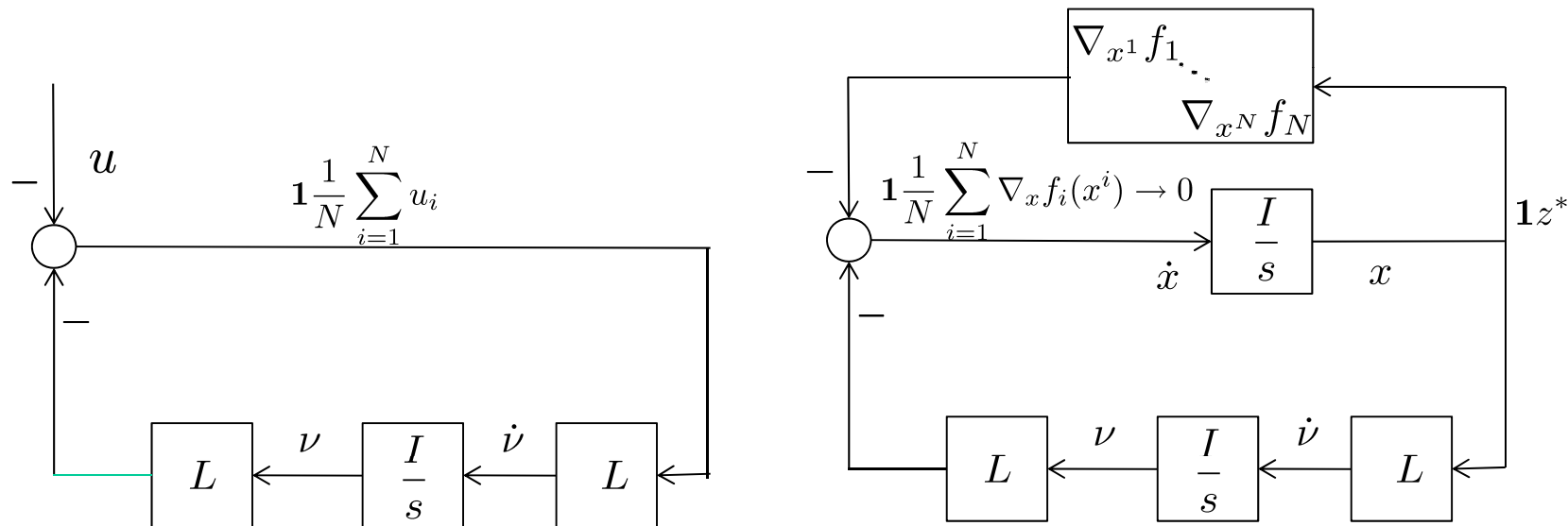


Switching topology + additive noise

# From Averaging To Optimization

$$z^* = \arg \min_z \sum_{i=1}^N f_i(z) \Rightarrow \sum_{i=1}^N \nabla_z f_i(z^*) = 0$$

$f_i(z)$  strictly convex



# Optimization Systems

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Convex Optimization Problem

$$p^* = \min_x f(x) \\ Ax = b$$

Lagrangian

$$F(x, \nu) = f(x) + \nu^T (Ax - b)$$

$$p^* = \max_{\nu} \min_x F(x, \nu)$$

Optimization System

$$\dot{x} = -\nabla_x F(x, \nu) = -\nabla_x f(x) - A^T \nu \\ \dot{\nu} = \nabla_{\nu} F(x, \nu) = Ax - b$$

Under mild conditions,  $\lim_{t \rightarrow \infty} x(t) = x^*, \quad \forall (x(0), \nu(0))$

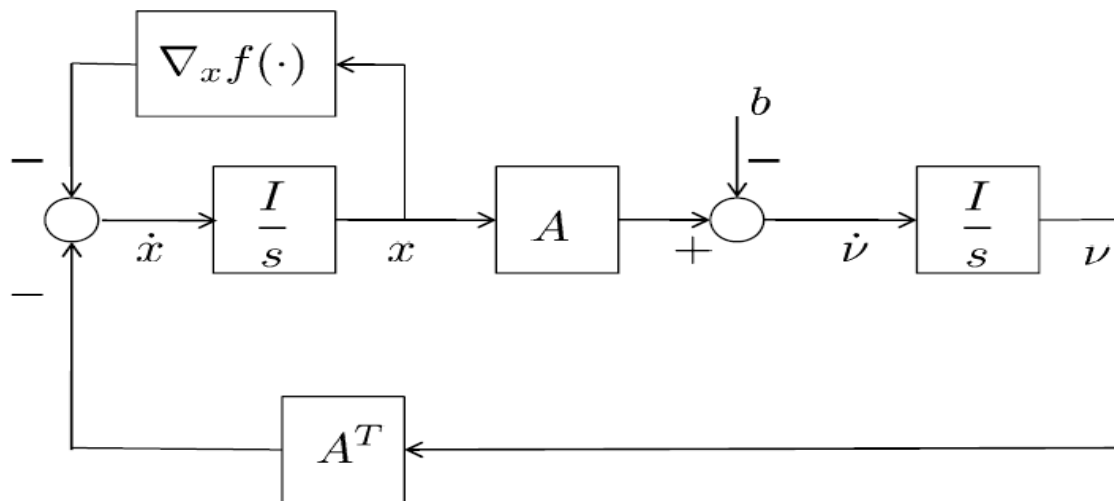


# Control Perspective

$$p^* = \min_x f(x) \\ Ax = b$$

$$\dot{x} = -\nabla_x f(x) - A^T \nu$$

$$\dot{\nu} = Ax - b$$



- ▶ Optimization system is a feedback dynamical system
- ▶ Subject to fundamental limitations of feedback
  - ▶ Tracking? Adaptation? Disturbance rejection?
- ▶ Multiplier dynamics as dynamic controller
- ▶ Controller design for optimization systems?
  - ▶ For quadratic programming problem, LTI theory applies!

# Distributed Optimization Systems

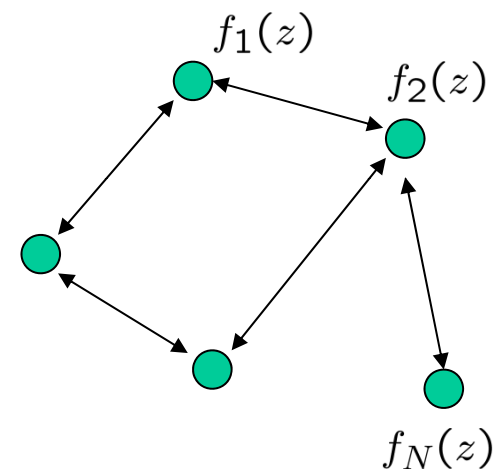
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Agent's private utility function (convex, differentiable)

$$f_i(z) : \mathbb{R} \rightarrow \mathbb{R} \quad (\text{for simplicity})$$

Problem: find optimal

$$z^* = \arg \min \sum_{i=1}^N f_i(z)$$



Arising in various applications

- ▶ Distributed tracking and localization
- ▶ Estimation over sensor networks
- ▶ Large scale optimization in machine learning
- ▶ Resource allocation...

# New Distributed Optimization System

$$\min_z \sum_{i=1}^N f_i(z) = \min_{\substack{x^i = x^j \\ \forall i, j}} \sum_{i=1}^N f_i(x^i) = \min_{L \begin{bmatrix} x^1 \\ \vdots \\ x^N \end{bmatrix} = 0} \sum_{i=1}^N f_i(x^i)$$

Undirected connected graph,  $L = L^T$

$$\min_{Lx=0} \sum_{i=1}^N f_i(x^i)$$

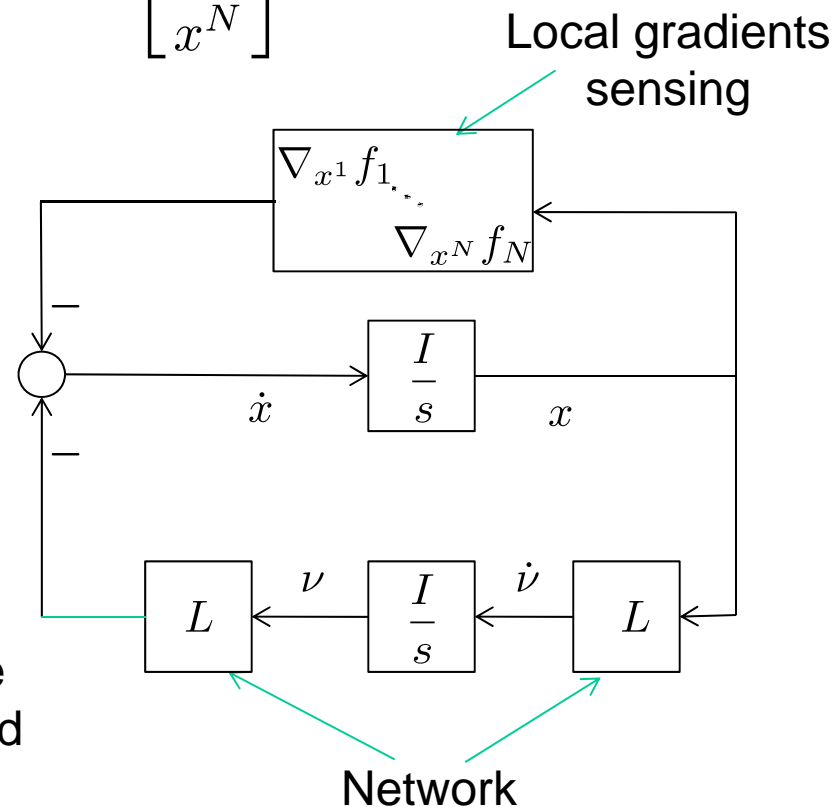
$$\begin{aligned} \dot{x} &= -\nabla_x f(x) - L^T \nu \\ \dot{\nu} &= Lx \end{aligned}$$

Related to MOM

Does not require centralized network node

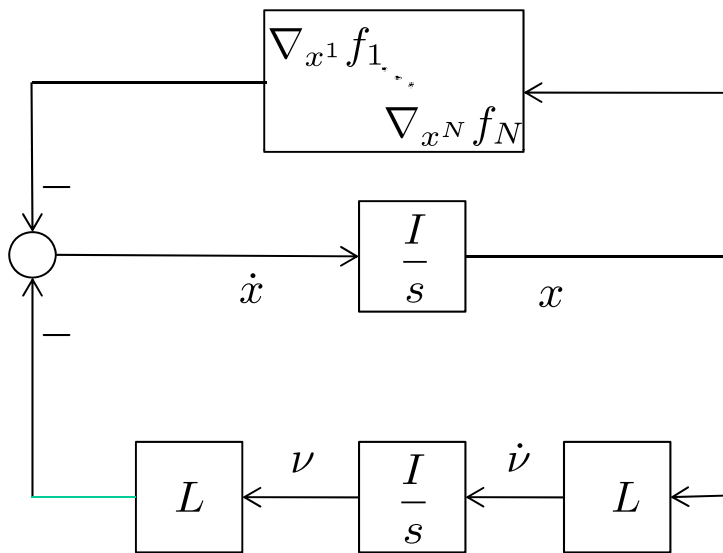
Different from alternating directions method

Implications for studying bio systems

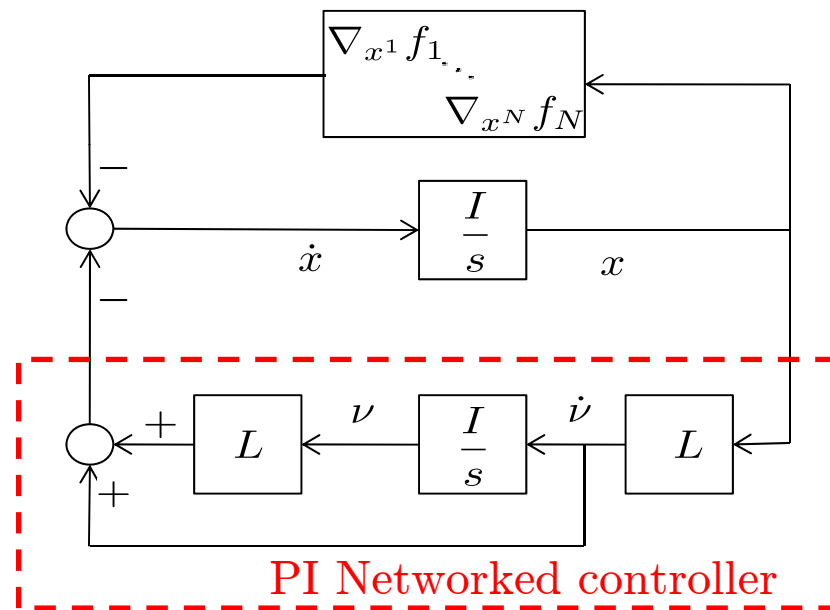


# Augmented Lagrangian and PI Control [Wang Elia Allerton 10]

$$p^* = \min_{Lx=0} \sum_{i=1}^N f_i(x^i)$$



$$p^* = \min_{Lx=0} \sum_{i=1}^N f_i(x^i) + x^T \frac{L}{2} x$$



- ▶ Augmented term introduces a proportion gain in the feedback loop
- ▶ Control interpretation of improved convergence of augmented method
- ▶ More powerful distributed controllers *realizable* over the network?

[Andalam, Elia CDC10, ACC 12]

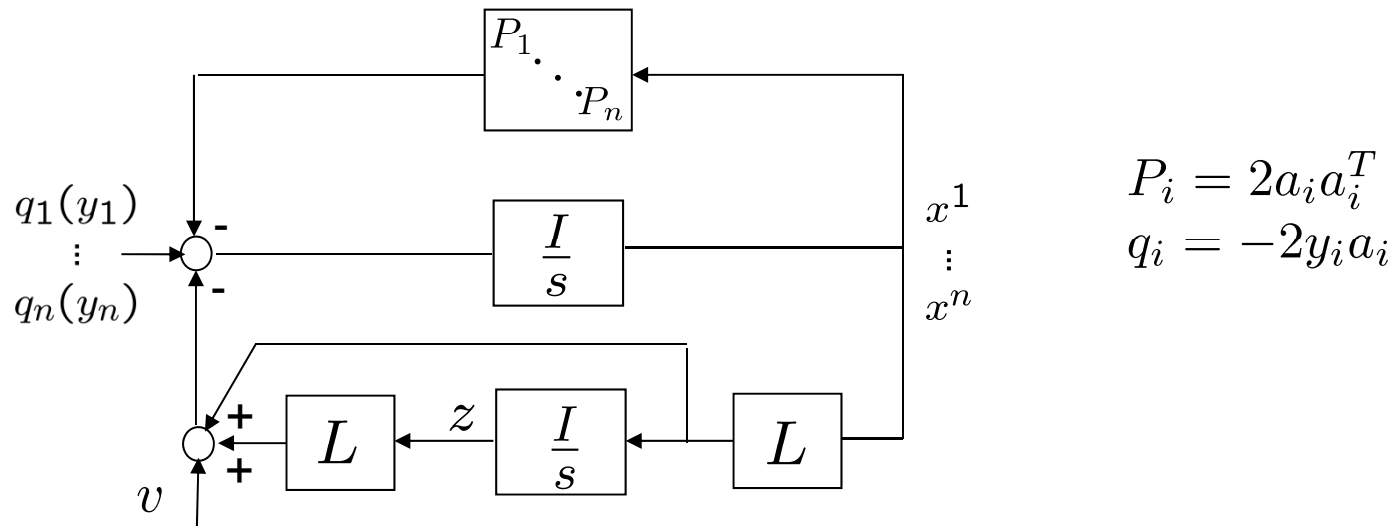
# Distributed Least Squares over Noisy Channels

N sensors want to collectively learn  $x \in \mathbb{R}^n$ , (location of a target)  
 Each sensor has inaccurate incomplete (scalar) measurements

$$y_i = a_i^T x + v_i, \quad v_i \sim N(0, 1)$$

Problem: distributedly find the optimal ML estimate  $x^*$

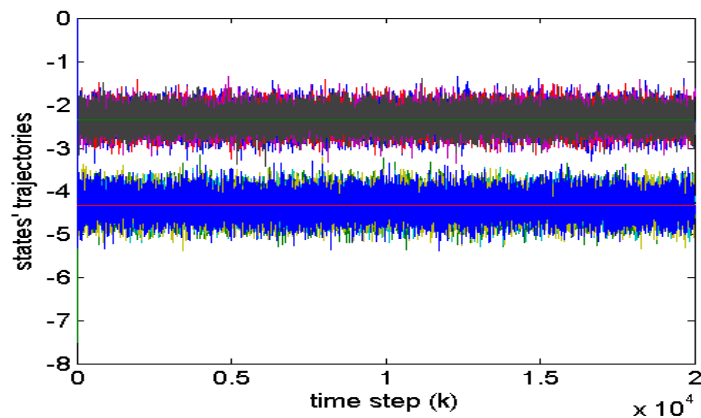
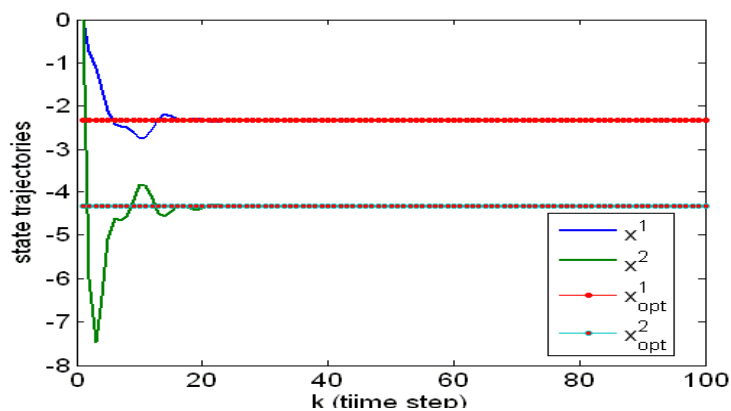
Solution : 
$$x^* = \arg \min_x \sum_{i=1}^n (a_i^T x - y_i)^2 = \arg \min_x \|Ax - y\|_2^2$$



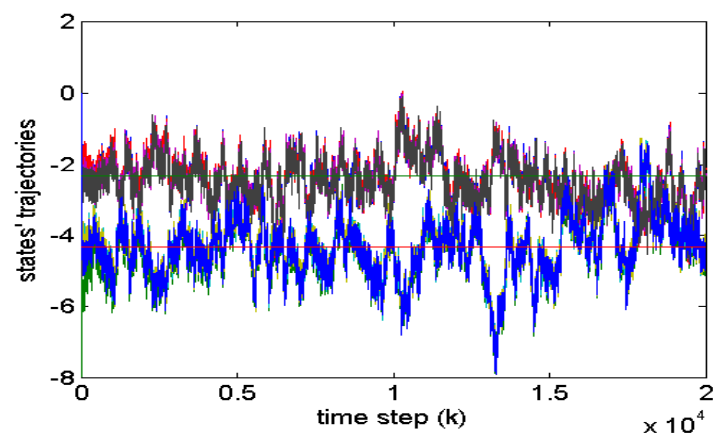
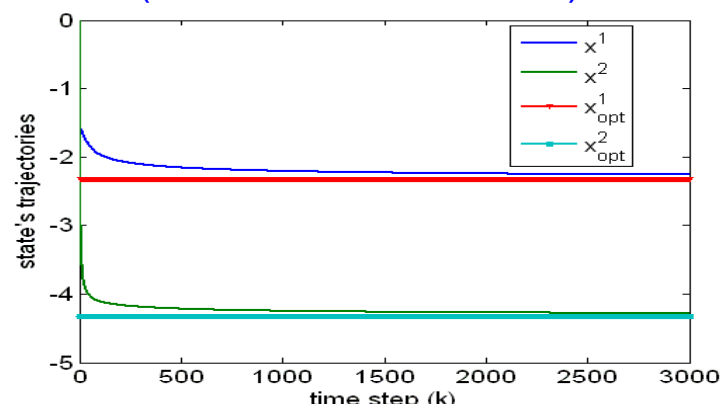
# Simulations: speed + robustness

Ring topology, four nodes, quadratic local utility

Our model (constant step-size)

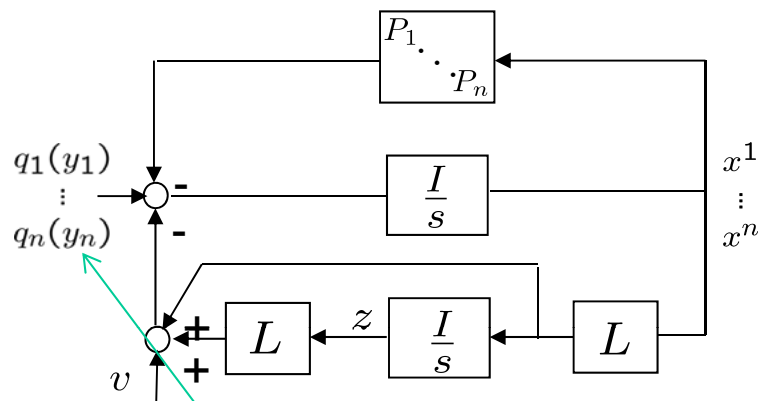


The gradient descent model  
(Nedic and Asuman 08)



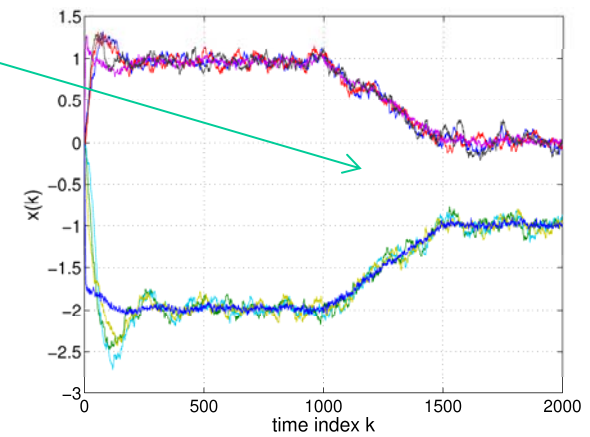
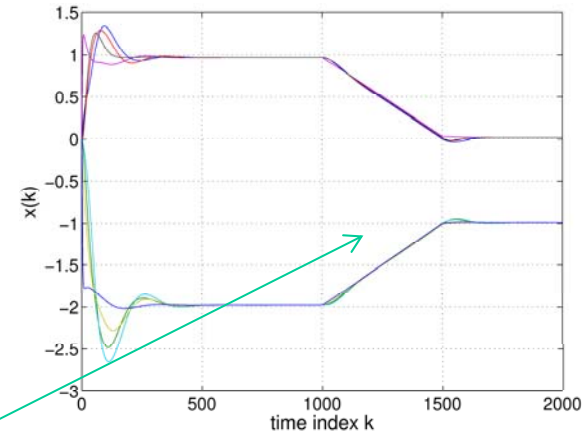
Double Laplacian robust network organization

# Real-time Adaptive Optimization



Changing measurements

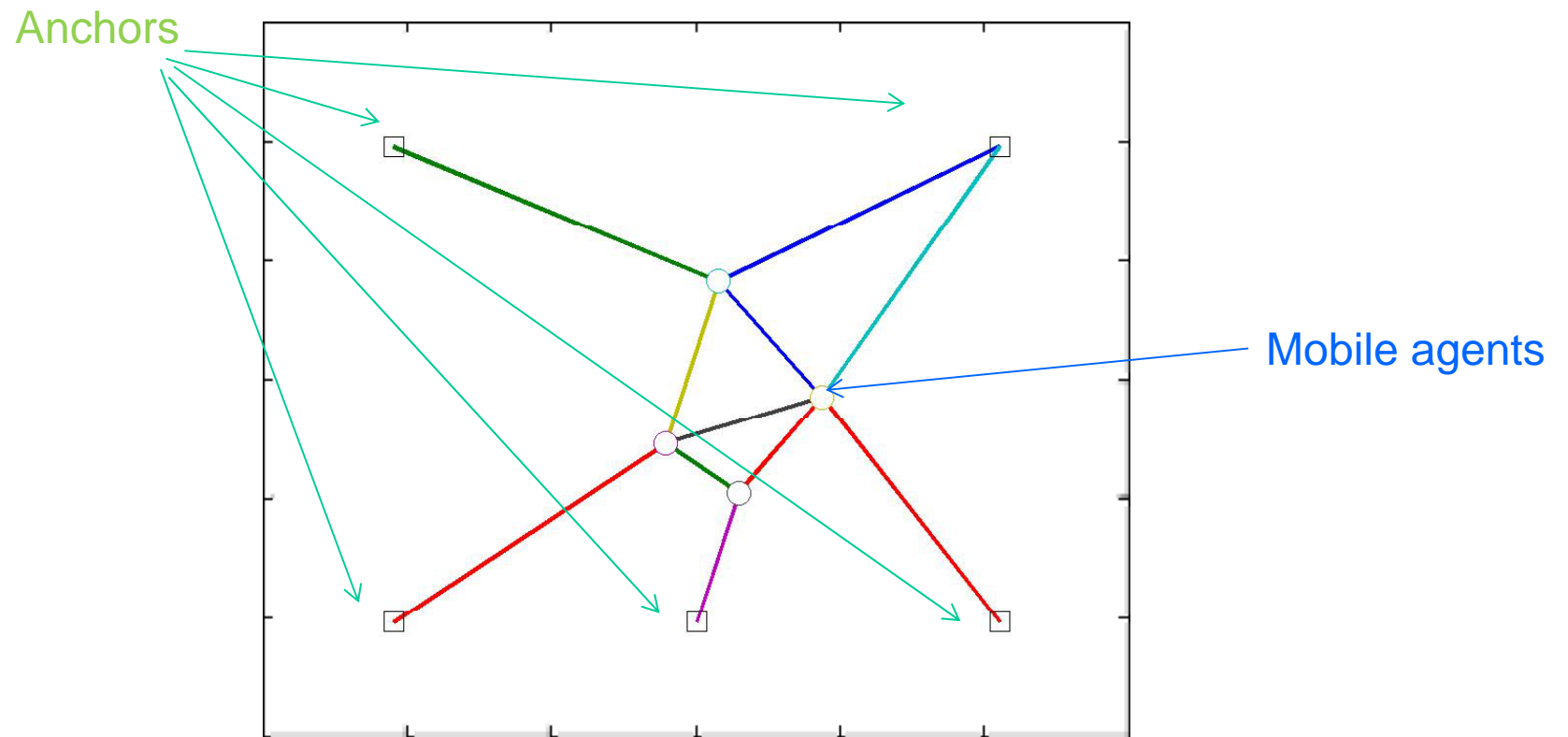
- ▶ Real-time adaptation to data
- ▶ Resilient to channel uncertainty [Wang, Elia ACC12]



Resilience to noise and packet-drops

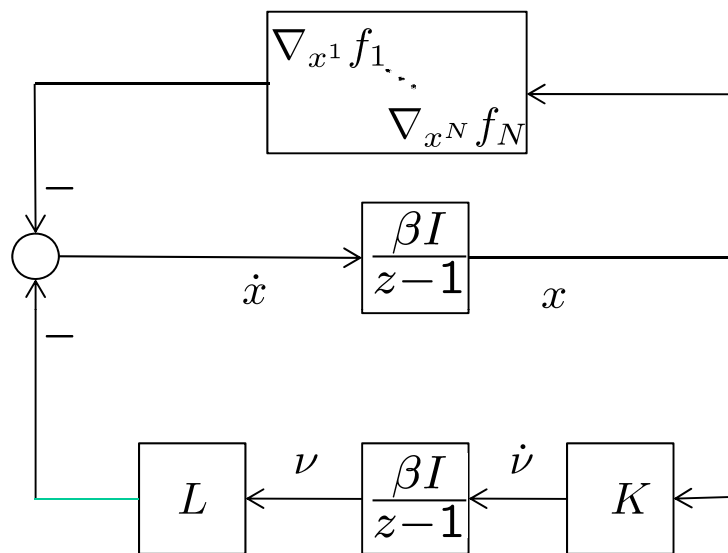
# Distributed Adaptive Optimal Placement

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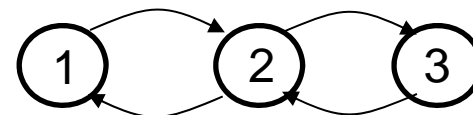
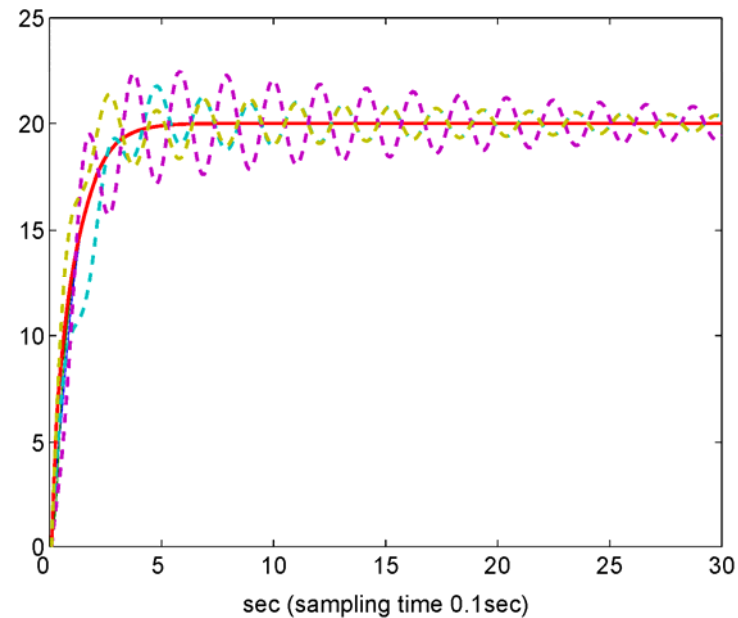




# Networked Controller Design?



Controller order [ 8,11,8]



Systematic design of controllers *realizable* over the network

[Andalam, Elia CDC10, ACC 12]

# Conclusions

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- ▶ Networked Systems offer many opportunities for new research on complex engineered and natural systems
- ▶ Key aspect: interplay between information and control
- ▶ Fading in communication channels is a main mechanism for emergence of complex behavior in networked systems
- ▶ A new control perspective on distributed optimization systems
- ▶ Moving toward a theory of distributed computation over unreliable networks.
- ▶ Distributed controller design for networked computational systems