

Analysis and Control of Multi-Agent Systems

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Control of Networks

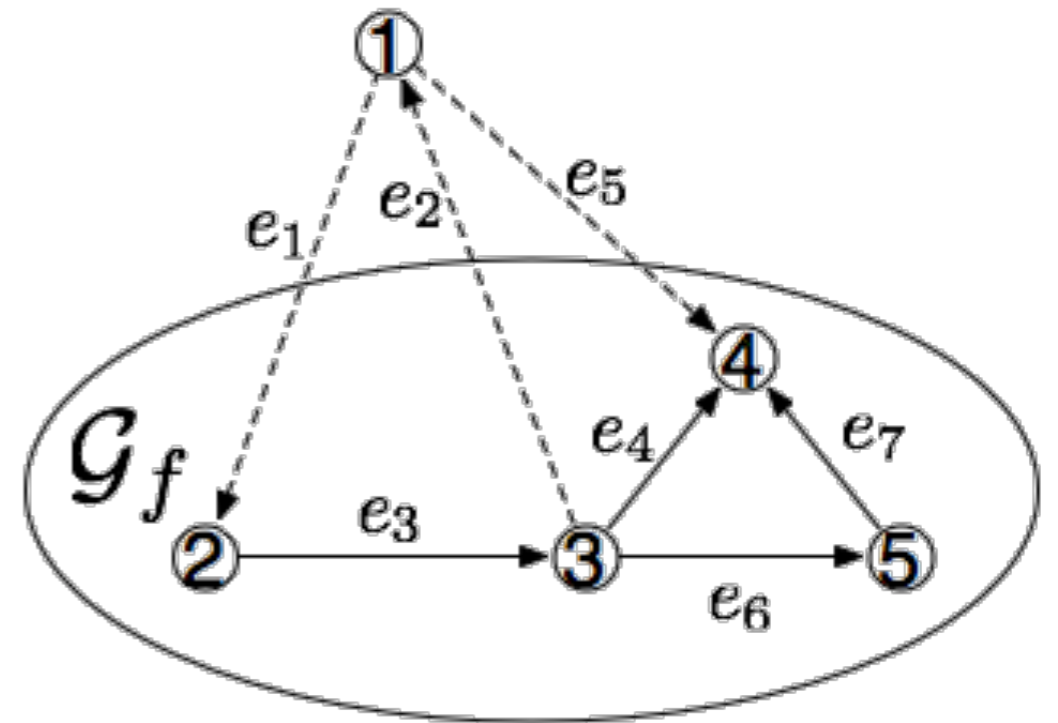
Edge Agreement and Consensus Performance



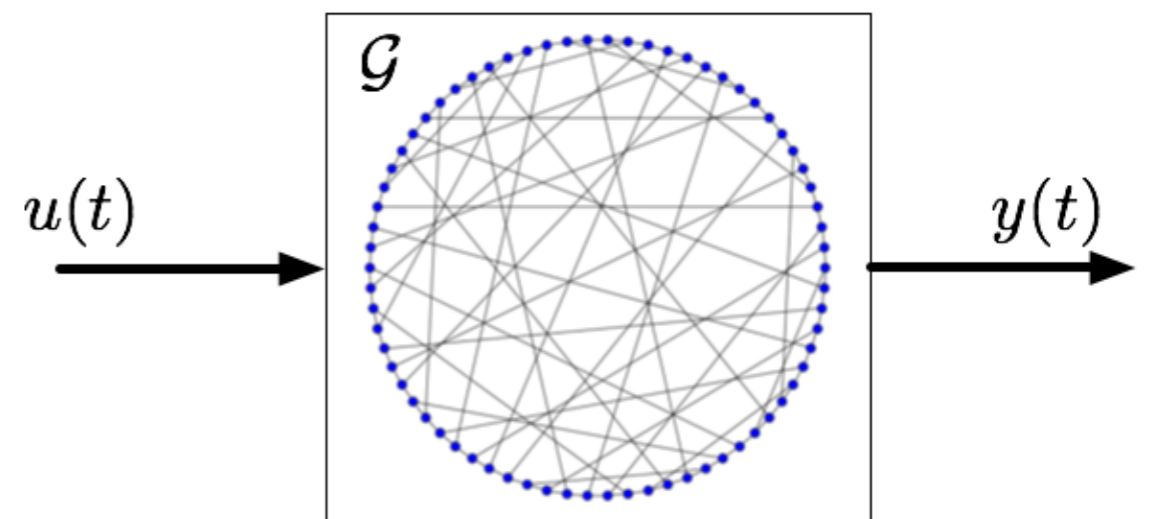
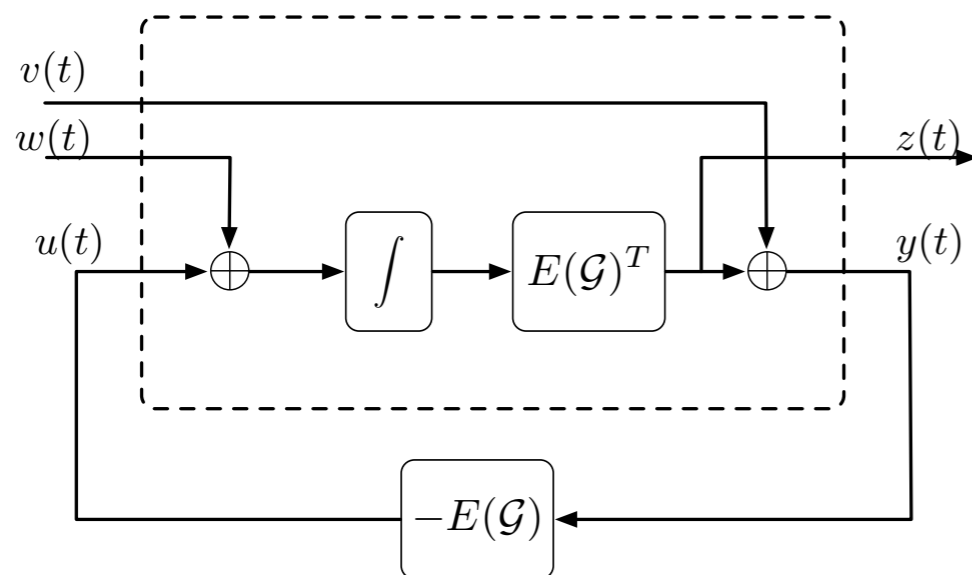
last time...

Controlled Agreement

- consensus protocol with a “rebel”
- input-output setup
- controllability

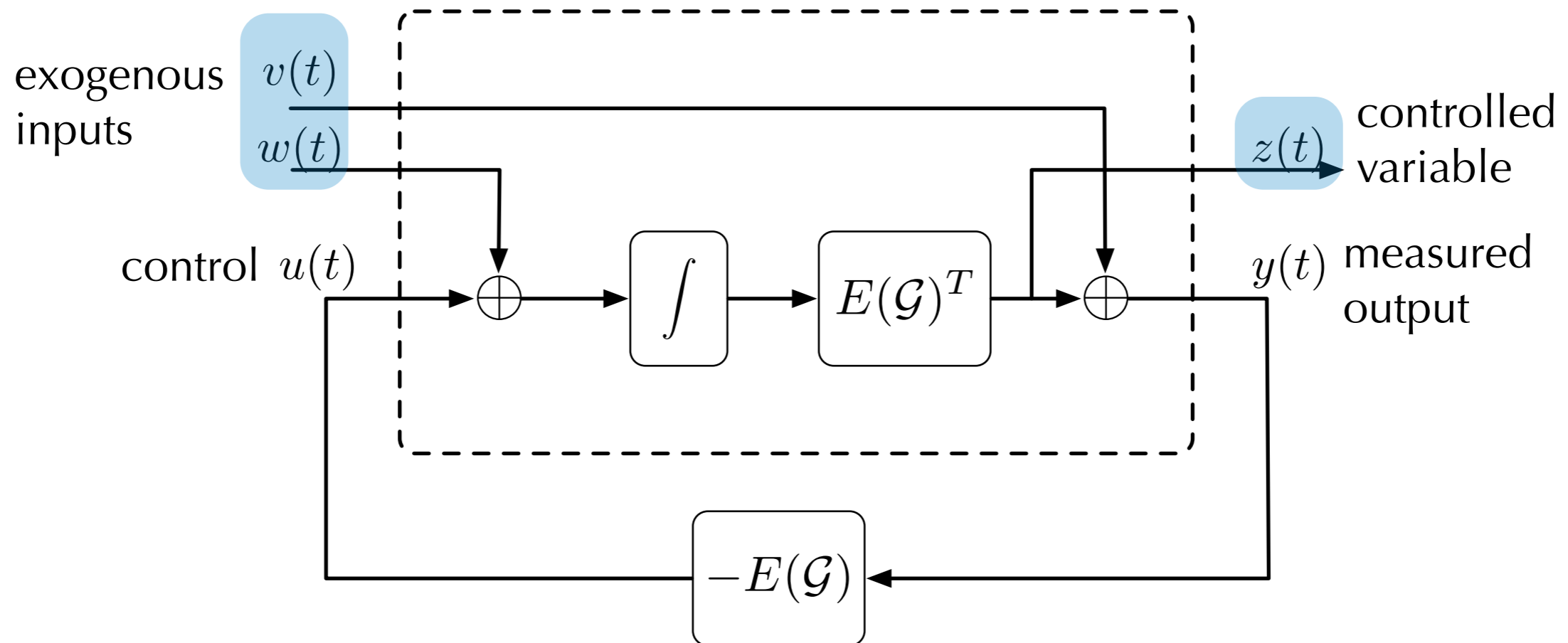


Performance of Consensus



Consensus with Exogenous Inputs

An 'input-output' consensus model

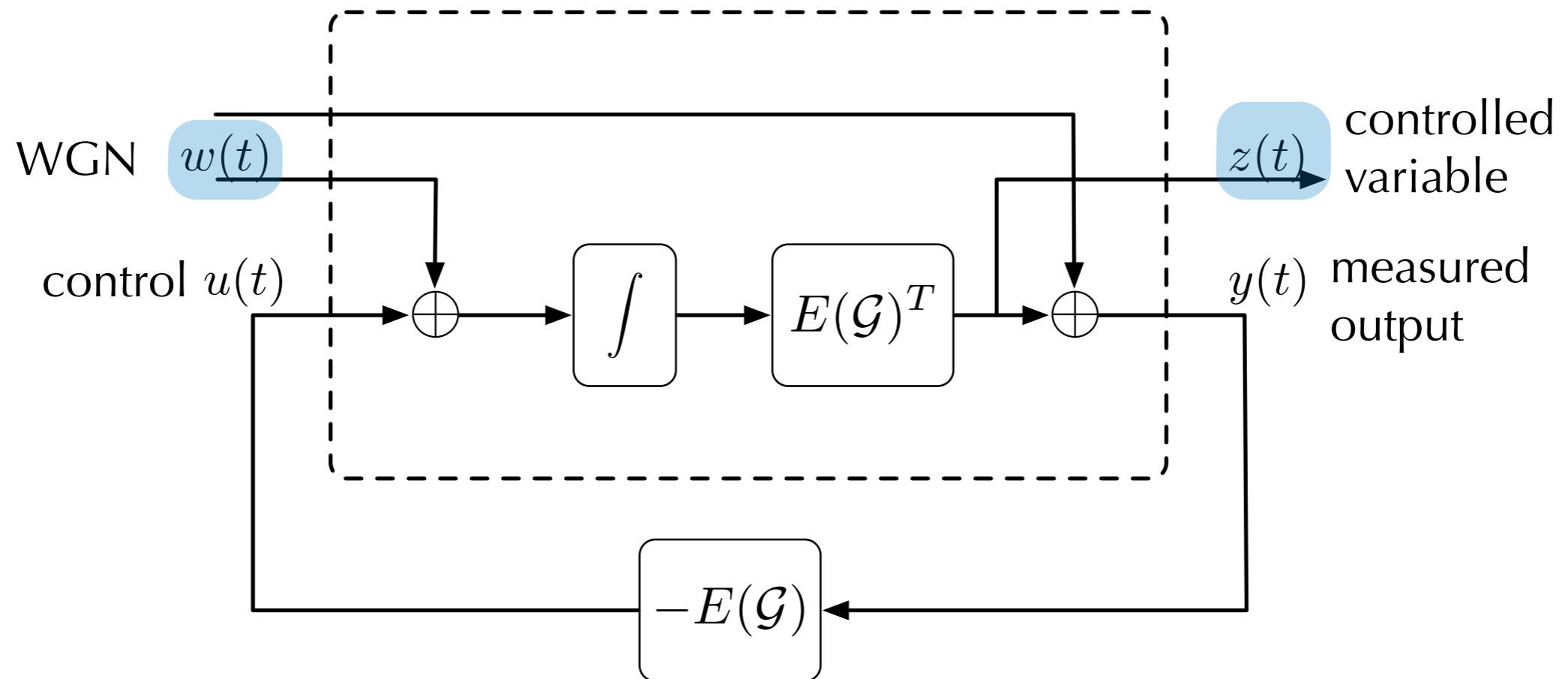


$$\Sigma(\mathcal{G}) : \begin{cases} \dot{x}(t) = -L(\mathcal{G})x(t) + \begin{bmatrix} I & -E(\mathcal{G}) \end{bmatrix} \begin{bmatrix} w(t) \\ v(t) \end{bmatrix} \\ z(t) = E(\mathcal{G})^T x(t). \end{cases}$$



Consensus with Exogenous Inputs

what happens when consensus is driven by Gaussian white noise?



$$\begin{cases} \dot{x}(t) &= -L(\mathcal{G})x(t) + w(t) \\ z(t) &= E(\mathcal{G})^T x(t) \end{cases}$$



Consensus with Exogenous Inputs

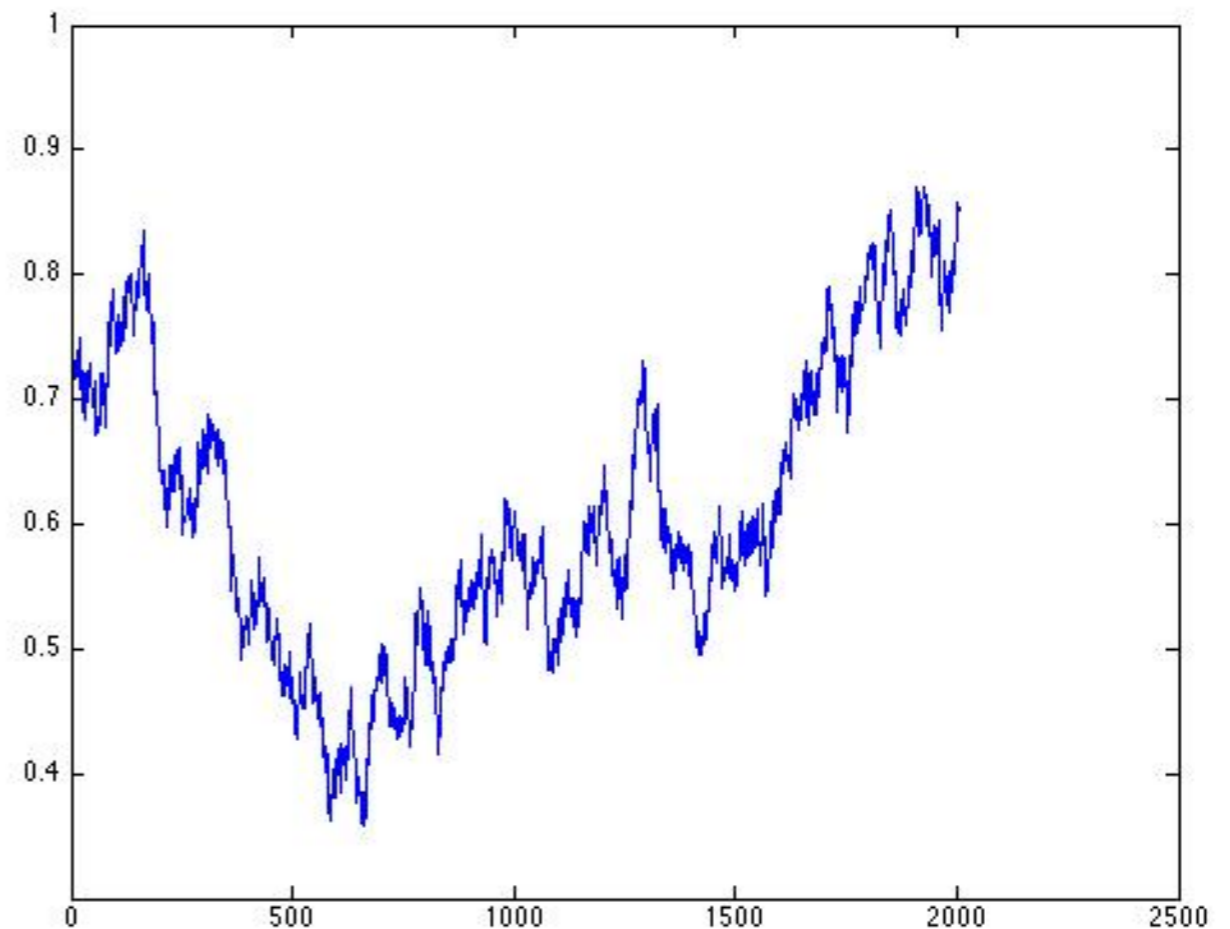
what happens when consensus is driven by Gaussian white noise?

$$\dot{\bar{x}}(t) = \frac{1}{n} \mathbf{1}^T w(t)$$

average is “driven” by noises...

$$\mathcal{E}(\bar{x}(t)^2) = \frac{\sigma_w^2}{n} t$$

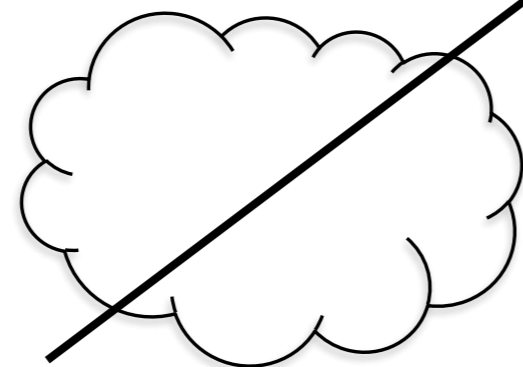
a random walk



Consensus with Exogenous Inputs

what happens when consensus is driven
by Gaussian white noise?

$$\mathcal{N}(E(\mathcal{G})^T) = \text{span}\{\mathbf{1}\}$$

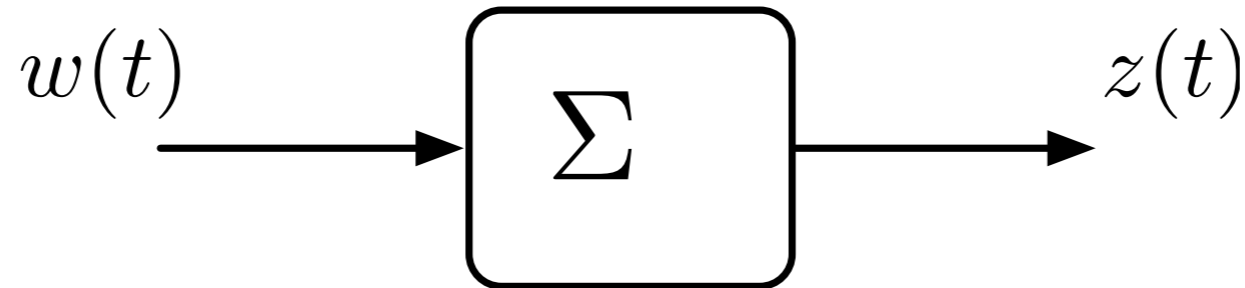


$$\mathcal{E}(y(t)^T y(t))$$

When driven by noise, it is meaningful to examine
how noises effect the stead-state covariance of the
relative states



\mathcal{H}_2 Performance of Linear Systems



A stable linear system

$$\Sigma \begin{cases} \dot{x}(t) & = Ax(t) + Bu(t) \\ y(t) & = Cx(t) \end{cases}$$

\mathcal{H}_2 System Norm

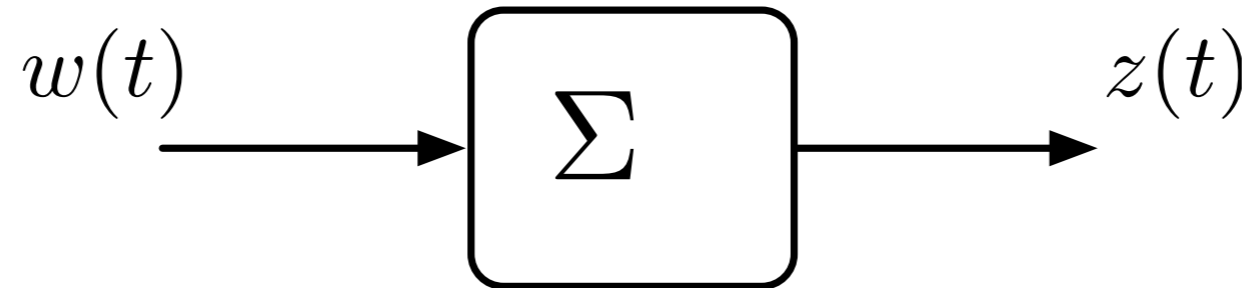
$$\|\Sigma\|_2 = \sqrt{\mathbf{trace} CPCT^T}$$

Controllability Gramian

$$P = \int_0^{\infty} e^{At} BB^T e^{A^T t} dt \quad AP + PA^T + BB^T = 0$$



\mathcal{H}_2 Performance of Linear Systems



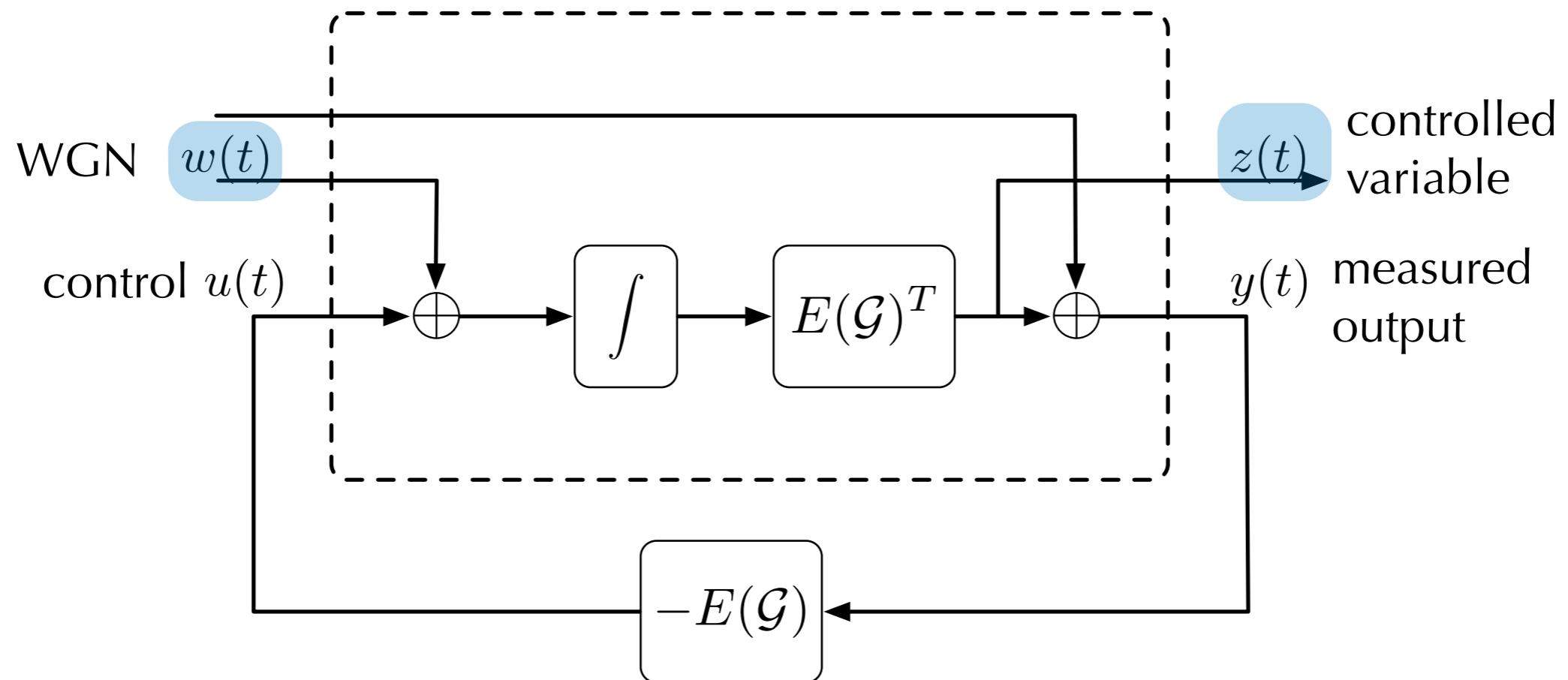
A stable linear system

$$\Sigma \begin{cases} \dot{x}(t) & = Ax(t) + Bu(t) \\ y(t) & = Cx(t) \end{cases}$$

for linear systems driven by white Gaussian noise, the \mathcal{H}_2 system norm can be interpreted as a *bound* on the *steady-state covariance* of the output



A Minimal Realization



$$S = \begin{bmatrix} P & \frac{1}{\sqrt{n}} \mathbb{1} \end{bmatrix}$$

$$\mathbb{1}^T P = 0$$

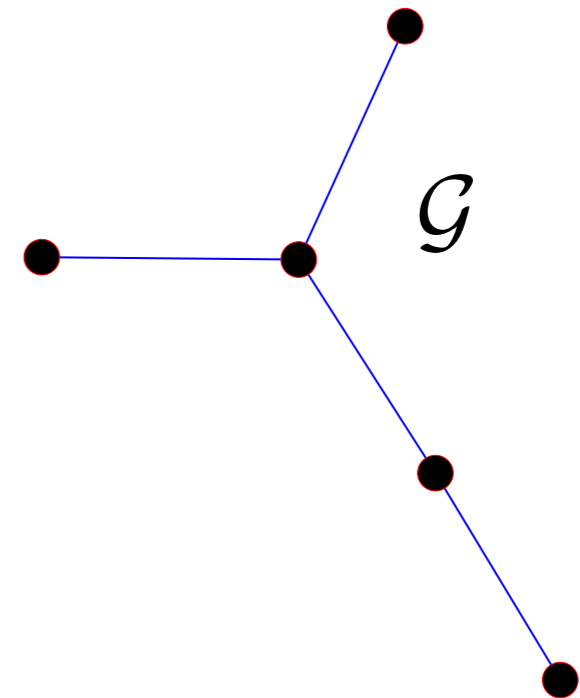
$$\tilde{x}(t) = S^{-1} x(t)$$

$$\begin{cases} \dot{\tilde{x}}(t) &= -S^{-1} L(\mathcal{G}) S \tilde{x}(t) + S^{-1} w(t) \\ z(t) &= E(\mathcal{G})^T S \tilde{x}(t) \end{cases}$$



A Minimal Realization

$$\begin{cases} \dot{\tilde{x}}(t) &= -S^{-1}L(\mathcal{G})S\tilde{x}(t) + S^{-1}w(t) \\ z(t) &= E(\mathcal{G})^T S\tilde{x}(t) \end{cases}$$



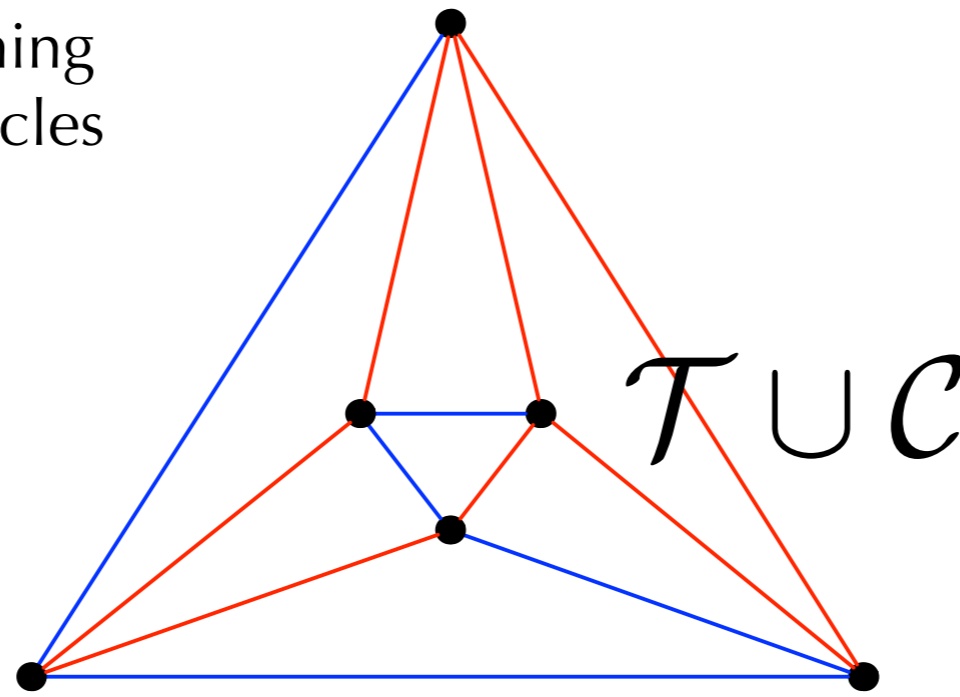
$$S = \left[\begin{array}{cccc|c} -0.45 & -0.45 & -0.45 & -0.45 & 0.45 \\ 0.86 & -0.14 & -0.14 & -0.14 & 0.45 \\ -0.14 & 0.86 & -0.14 & -0.14 & 0.45 \\ -0.14 & -0.14 & 0.86 & -0.14 & 0.45 \\ -0.14 & -0.14 & -0.14 & 0.86 & 0.45 \end{array} \right]$$

$$S^{-1}L(\mathcal{G})S = \left[\begin{array}{cccc|c} 2.90 & 0.90 & 0.90 & -0.40 & 0.00 \\ 0.90 & 1.90 & 0.90 & 0.60 & 0.00 \\ 0.90 & 0.90 & 1.90 & 0.60 & -0.00 \\ -0.40 & 0.60 & 0.60 & 1.29 & -0.00 \\ \hline 0.00 & 0.00 & 0.00 & 0.00 & -0.00 \end{array} \right]$$



Spanning Trees and Cycles

A graph as the union of a spanning tree and edges that complete cycles



a spanning tree

remaining edges
"complete cycles"

$$E(\mathcal{G}) = E(\mathcal{T}) \underbrace{\begin{bmatrix} I & T_{(\mathcal{T}, \mathcal{C})} \end{bmatrix}}_{\mathcal{R}_{(\mathcal{T}, \mathcal{C})}}$$

Cycles are a "linear combination" of edges in a spanning tree

$$T_{(\mathcal{T}, \mathcal{C})} = \underbrace{(E_{\mathcal{T}}^T E_{\mathcal{T}})^{-1} E_{\mathcal{T}}^T}_{E_{\mathcal{T}}^L} E(\mathcal{C})$$

$\mathcal{R}_{(\mathcal{T}, \mathcal{C})}$ rows form a basis for the *cut space* of the graph



Edge Laplacian

$$\begin{cases} \dot{\tilde{x}}(t) &= -S^{-1}L(\mathcal{G})S\tilde{x}(t) + S^{-1}w(t) \\ z(t) &= E(\mathcal{G})^T S\tilde{x}(t) \end{cases}$$

$$\begin{bmatrix} x_{\mathcal{T}}(t) \\ \bar{x}(t) \end{bmatrix} = \underbrace{\begin{bmatrix} E(\mathcal{T})^T \\ \frac{1}{n}\mathbb{1}^T \end{bmatrix}}_{S^{-1}} x(t)$$

$$\begin{bmatrix} \dot{x}_{\mathcal{T}}(t) \\ \dot{\bar{x}}(t) \end{bmatrix} = \begin{bmatrix} (E(\mathcal{T})^T E(\mathcal{T})) \mathcal{R}_{(\mathcal{T},c)} \mathcal{R}_{(\mathcal{T},c)}^T & \mathbf{0} \\ \mathbf{0} & 0 \end{bmatrix} x(t) \begin{bmatrix} x_{\mathcal{T}}(t) \\ \bar{x}(t) \end{bmatrix} + \begin{bmatrix} E(\mathcal{T})^T \\ \frac{1}{n}\mathbb{1}^T \end{bmatrix} w(t)$$



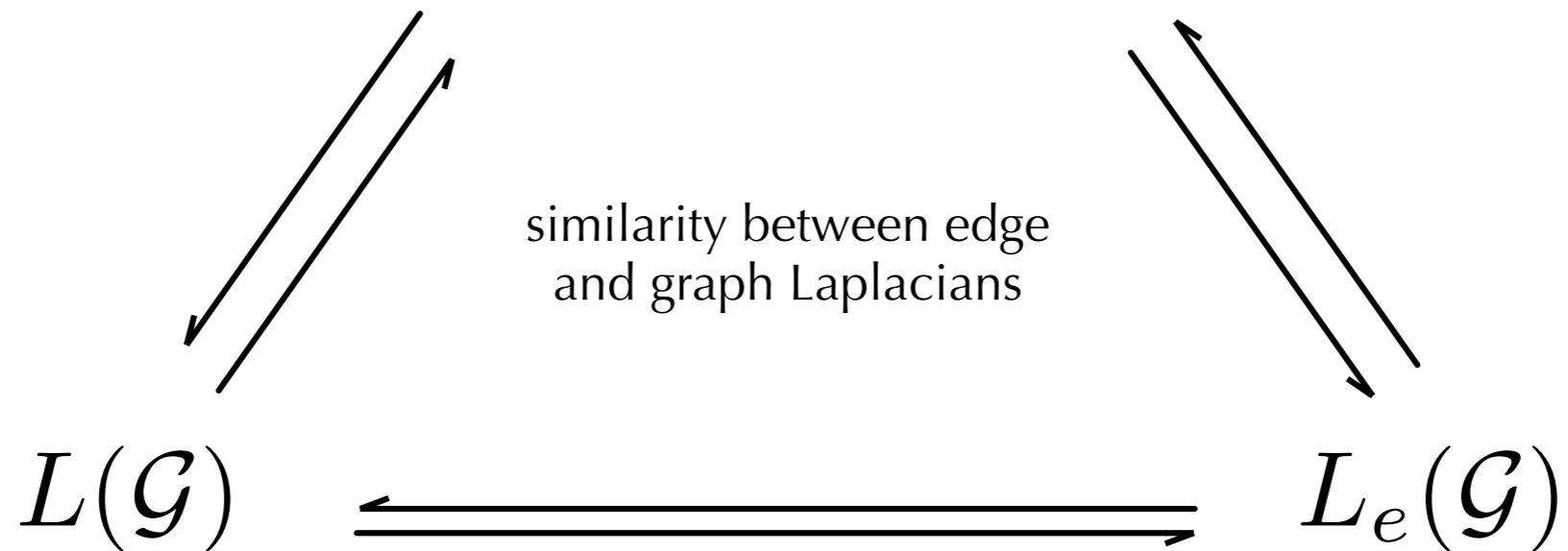
Edge Laplacian

Edge Laplacian

$$L_e(\mathcal{G}) = E(\mathcal{G})^T E(\mathcal{G})$$

Essential Edge Laplacian

$$L_e(\mathcal{T}) \mathcal{R}_{(\mathcal{T}, \mathcal{C})} \mathcal{R}_{(\mathcal{T}, \mathcal{C})}^T$$



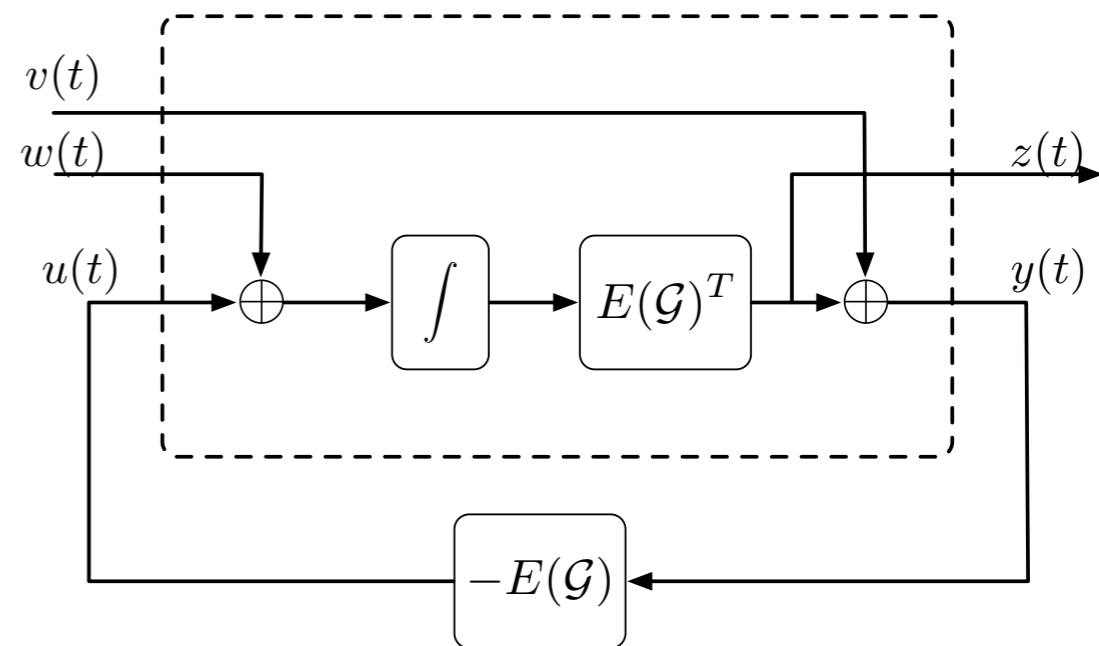
The Edge Agreement Problem

$$\Sigma(\mathcal{G}) : \begin{cases} \dot{x}(t) = -L(\mathcal{G})x(t) + \begin{bmatrix} I & -E(\mathcal{G}) \end{bmatrix} \begin{bmatrix} w(t) \\ v(t) \end{bmatrix} \\ z(t) = E(\mathcal{G})^T x(t). \end{cases}$$

$$x_e(t) = \begin{bmatrix} E(\mathcal{T})^T \\ \frac{1}{n} \mathbf{1}^T \end{bmatrix} x(t)$$



$$\Sigma_e(\mathcal{G}) : \begin{cases} \dot{x}_\tau(t) = -L_e(\mathcal{T})R_{(\mathcal{T},c)}R_{(\mathcal{T},c)}^T x_\tau(t) + \\ \begin{bmatrix} E(\mathcal{T})^T & -L_e(\mathcal{T})R_{(\mathcal{T},c)} \end{bmatrix} \begin{bmatrix} w(t) \\ v(t) \end{bmatrix} \\ z(t) = x_\tau(t). \end{cases}$$

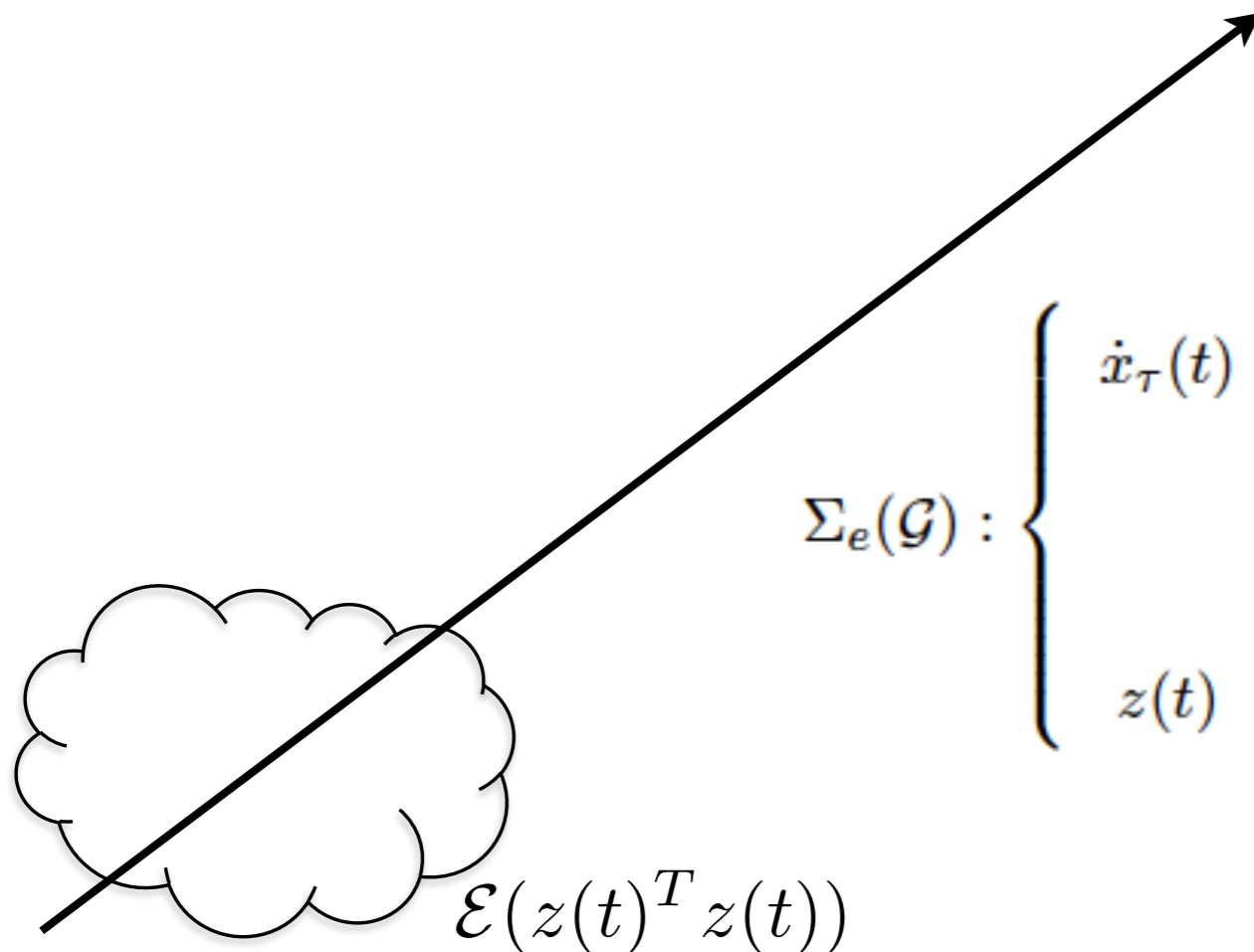


stable and minimal
realization of
consensus protocol



Consensus with Exogenous Inputs

$$\mathcal{N}(E(\mathcal{G})^T) = \text{span}\{\mathbf{1}\}$$


$$\Sigma_e(\mathcal{G}) : \begin{cases} \dot{x}_\tau(t) = -L_e(\mathcal{T})R_{(\mathcal{T},c)}R_{(\mathcal{T},c)}^T x_\tau(t) + \\ \left[E(\mathcal{T})^T \quad -L_e(\mathcal{T})R_{(\mathcal{T},c)} \right] \begin{bmatrix} w(t) \\ v(t) \end{bmatrix} \\ z(t) = x_\tau(t). \end{cases}$$

Performance of edge agreement problem can be used to study how noises affect the relative-state output



\mathcal{H}_2 Performance of Edge Agreement

Theorem

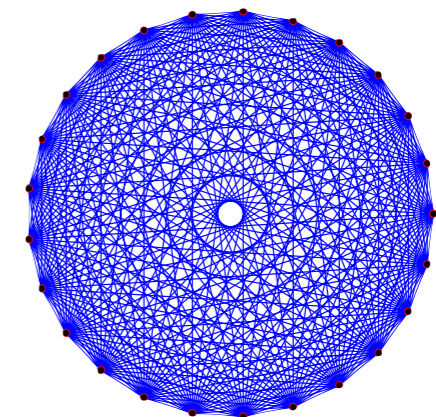
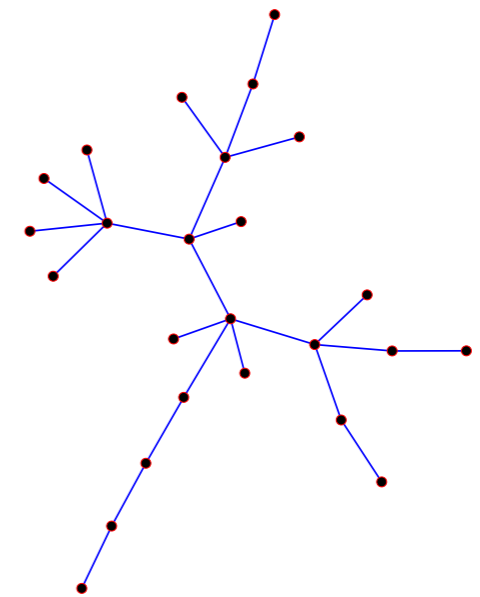
$$\|\Sigma_e(\mathcal{G})\|_2^2 = \frac{1}{2} \text{tr} \left[(R_{(\mathcal{T},c)} R_{(\mathcal{T},c)}^T)^{-1} \right] + (n - 1)$$

some immediate bounds...

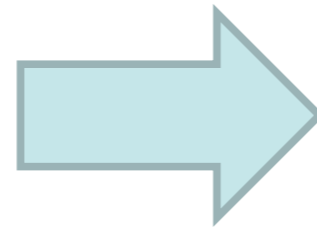
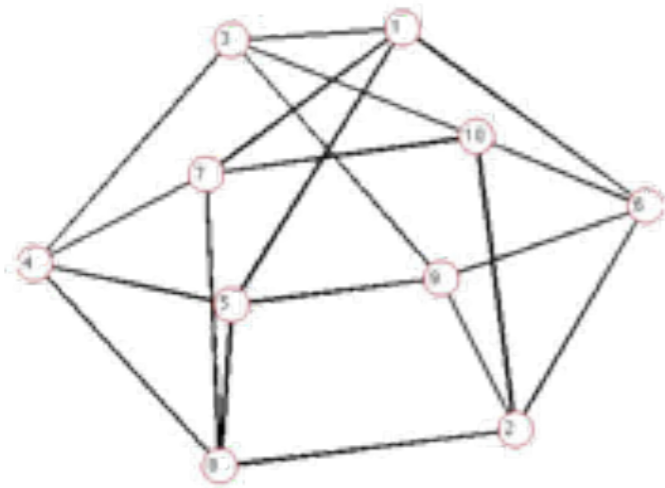
$$\|\Sigma_e(\mathcal{G})\|_2^2 \leq \|\Sigma_e(\mathcal{T})\|_2^2 = \frac{3}{2}(n - 1)$$

all trees are the same

$$\|\Sigma_e(\mathcal{G})\|_2^2 \geq \|\Sigma_e(K_n)\|_2^2 = \frac{n^2 - 1}{n}$$

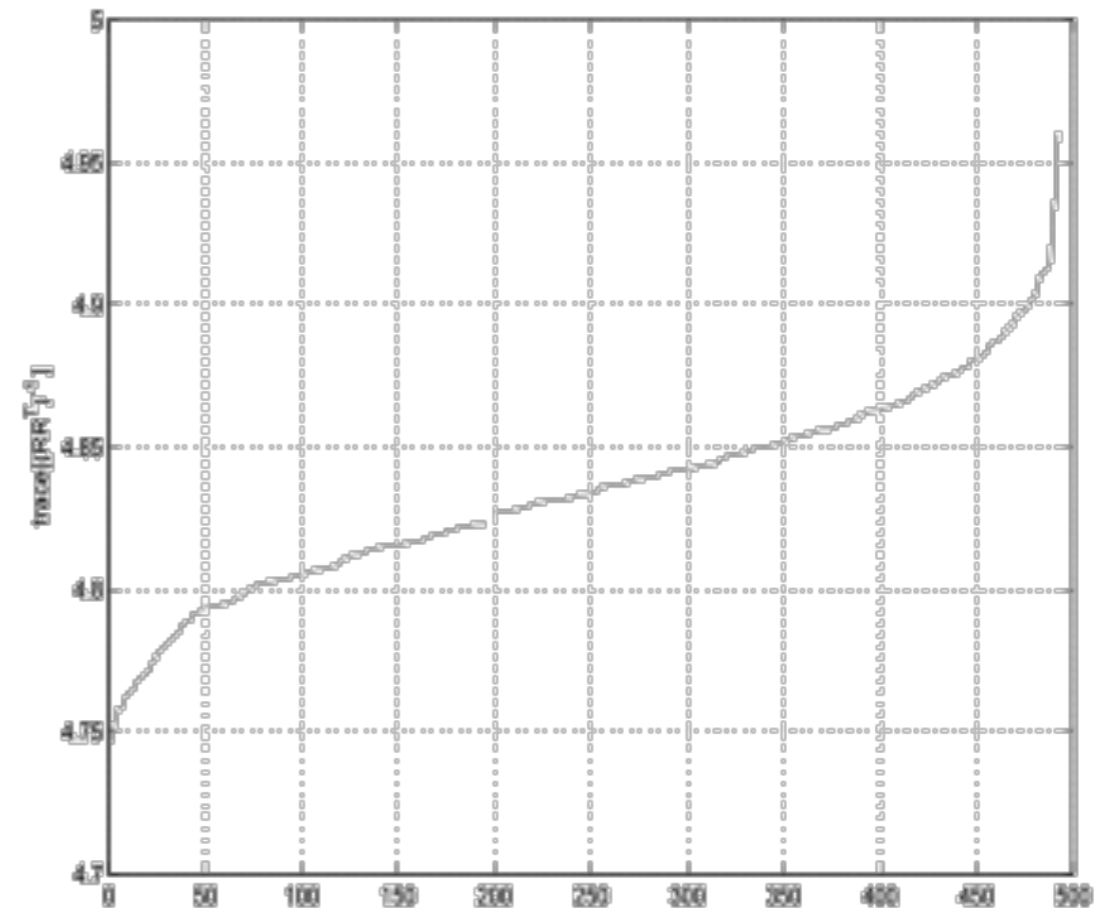


for general k -regular graphs...



dependant on structure
and cycles

$$\text{trace} \left[(RR^T)^{-1} \right]$$



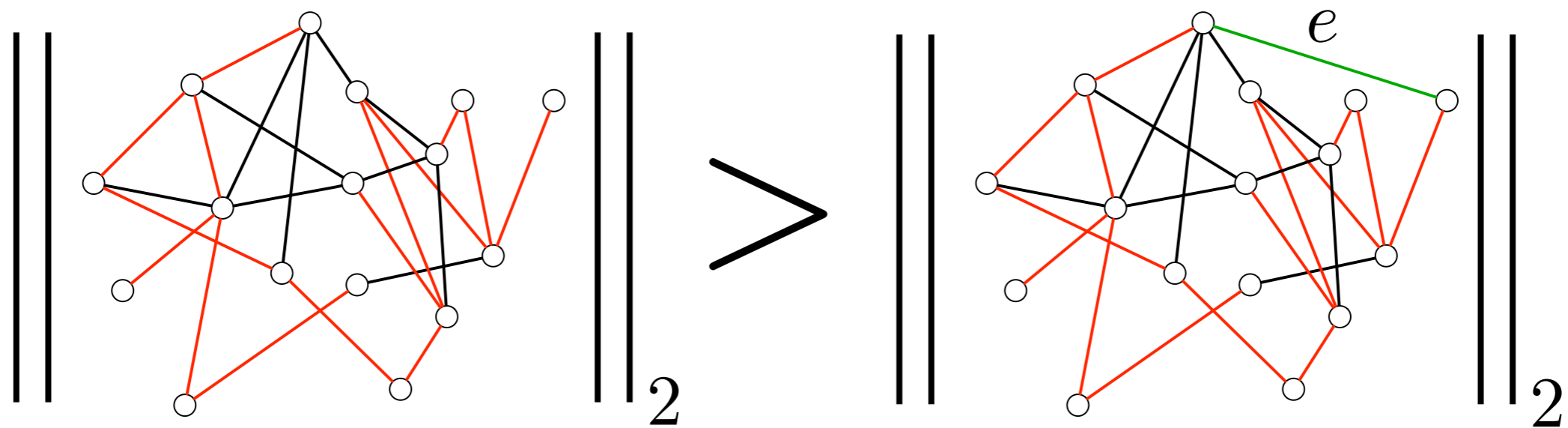
500 random 5-regular graphs



\mathcal{H}_2 Performance of Edge Agreement

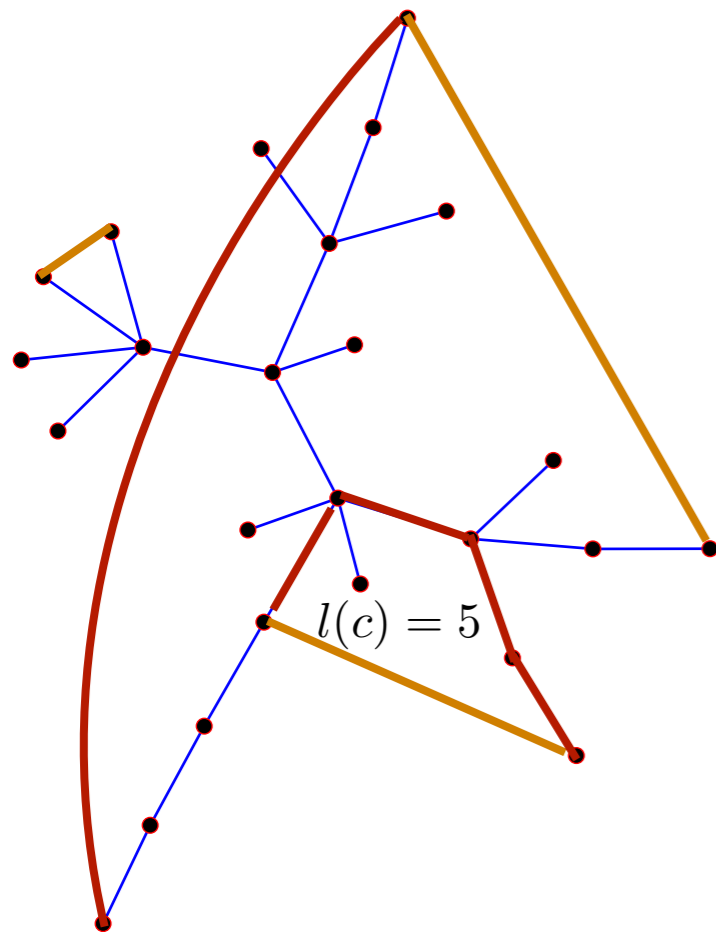
Theorem: Adding cycles always improves the performance.

$$\|\Sigma_e(\mathcal{G} \cup e)\|_2^2 = \|\Sigma_e(\mathcal{G})\|_2^2 - \frac{\left(R_{(\mathcal{T},c)}R_{(\mathcal{T},c)}^T\right)^{-1}cc^T\left(R_{(\mathcal{T},c)}R_{(\mathcal{T},c)}^T\right)^{-1}}{2\left(1+c^T\left(R_{(\mathcal{T},c)}R_{(\mathcal{T},c)}^T\right)^{-1}c\right)}$$



Performance and Cycles

Is there a *combinatorial* feature that affects the performance?



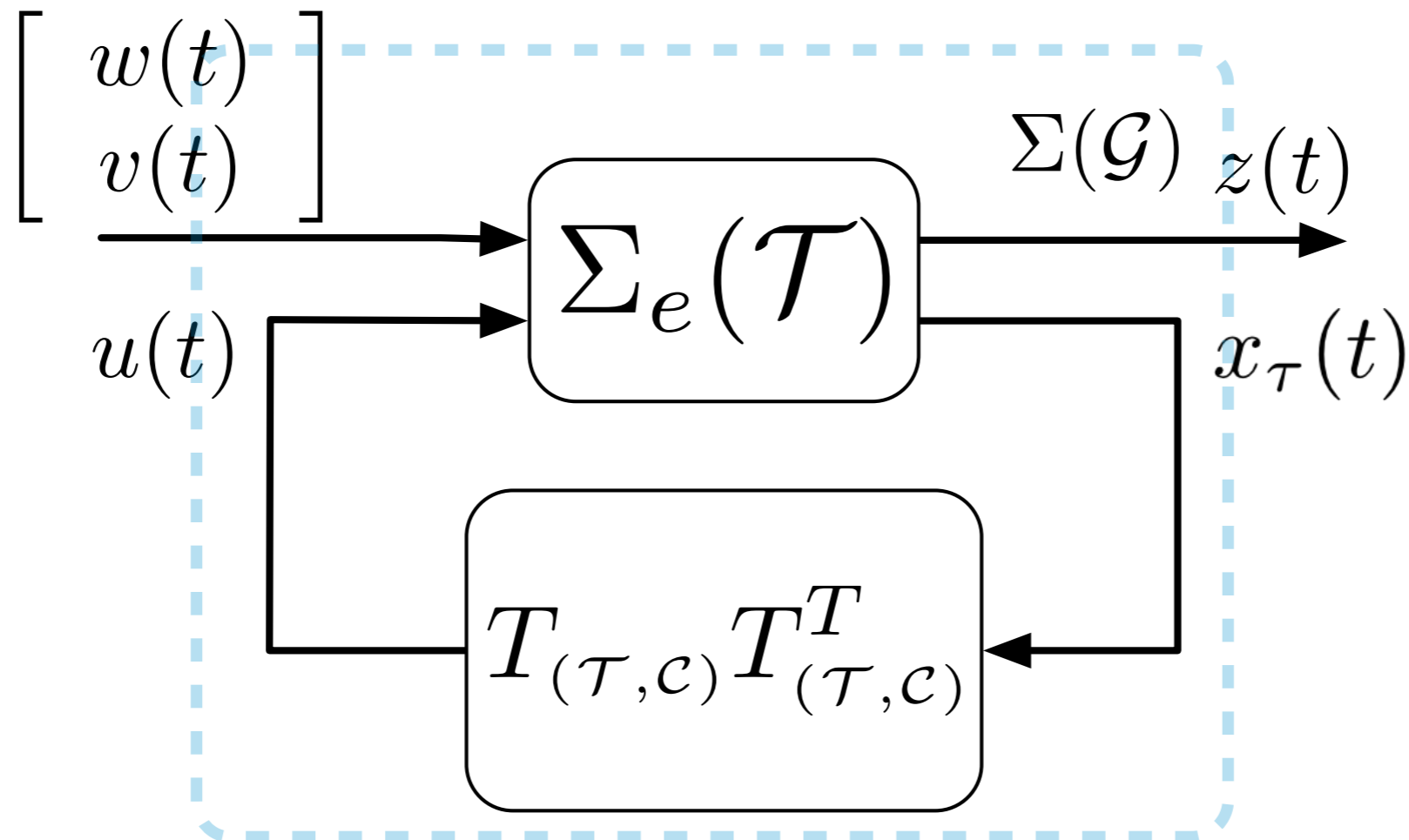
Corollary

$$\|\Sigma_e(\mathcal{T} \cup e)\|_2^2 = \|\Sigma_e(\mathcal{T})\|_2^2 - \frac{1}{2}(1 - l(c)^{-1})$$

long cycles are “better”



Cycles as Feedback



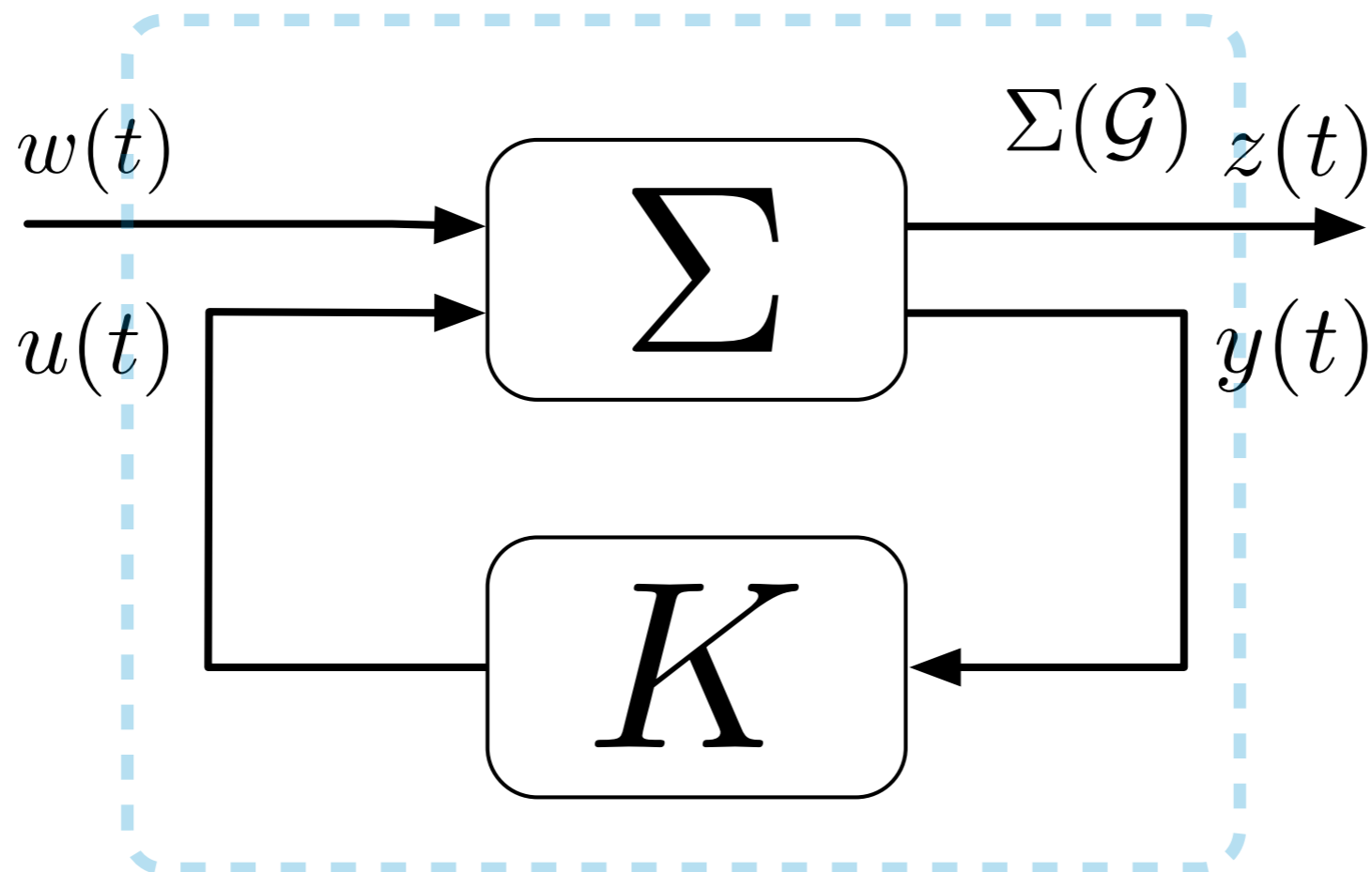
$$R_{(\tau, c)} = \begin{bmatrix} I & T_{(\tau, c)} \end{bmatrix}$$

$$E(\mathcal{T})T_{(\tau, c)} = E(\mathcal{C})$$

$$L_e(\mathcal{T})R_{(\tau, c)}R_{(\tau, c)}^T = L_e(\mathcal{T}) + \underline{L_e(\mathcal{T})T_{(\tau, c)}T_{(\tau, c)}^T}$$



Cycles as Feedback



$$R_{(\mathcal{T}, \mathcal{C})} = \begin{bmatrix} I & T_{(\mathcal{T}, \mathcal{C})} \end{bmatrix}$$

$$E(\mathcal{T})T_{(\mathcal{T}, \mathcal{C})} = E(\mathcal{C})$$

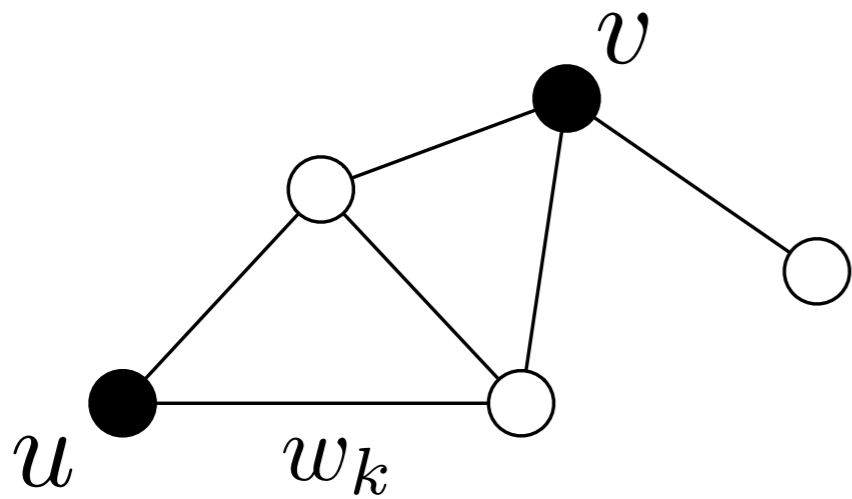
Design of consensus networks can be viewed as a state-feedback problem

$$L_e(\mathcal{T})R_{(\mathcal{T}, \mathcal{C})}R_{(\mathcal{T}, \mathcal{C})}^T = L_e(\mathcal{T}) + L_e(\mathcal{T})\underline{T_{(\mathcal{T}, \mathcal{C})}T_{(\mathcal{T}, \mathcal{C})}^T}$$

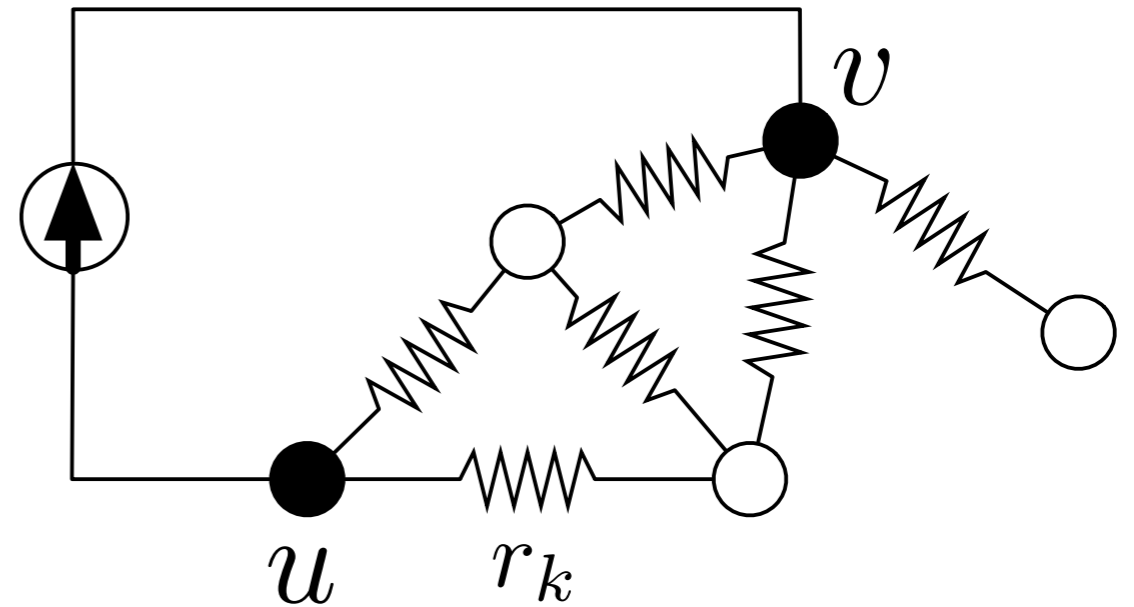


Effective Resistance of a Graph

The **effective resistance** between two nodes u and v is the electrical resistance measured across the nodes when the graph represents an electrical circuit with each edge a resistor



$r_k = \frac{1}{w_k}$ edge weights are the conductance of each resistor



$$\begin{aligned} r_{uv} &= (\mathbf{e}_u - \mathbf{e}_v)^T L^\dagger(\mathcal{G})(\mathbf{e}_u - \mathbf{e}_v) \\ &= [L^\dagger(\mathcal{G})]_{uu} - 2[L^\dagger(\mathcal{G})]_{uv} + [L^\dagger(\mathcal{G})]_{vv} \end{aligned}$$

Klein and Randić
1993



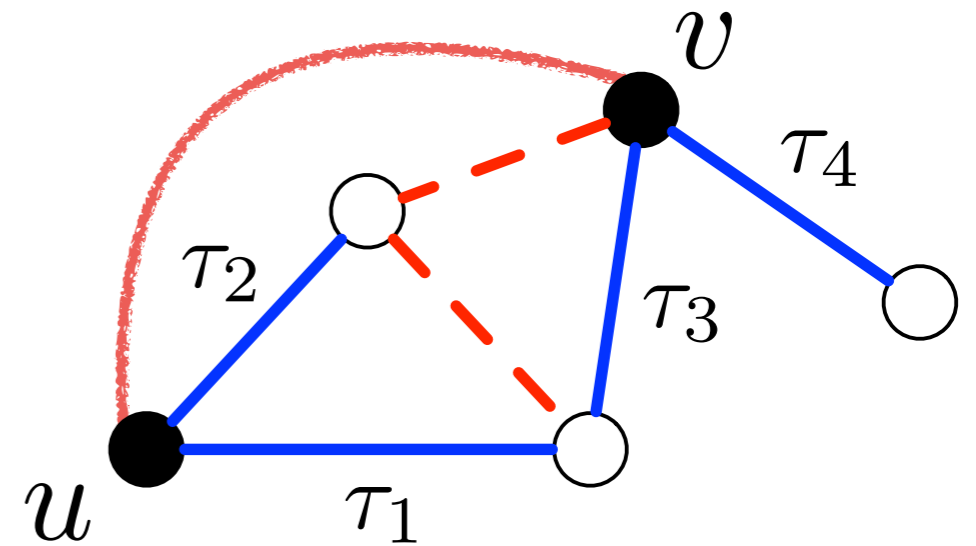
Effective Resistance of a Graph

Proposition 1

$$L^\dagger(\mathcal{G}) = (E_\tau^L)^T (R_{(\tau, c)} W R_{(\tau, c)}^T)^{-1} E_\tau^L$$

$$r_{uv} = (\mathbf{e}_u - \mathbf{e}_v)^T L^\dagger(\mathcal{G}) (\mathbf{e}_u - \mathbf{e}_v)$$

$$E_\tau^L(\mathbf{e}_u - \mathbf{e}_v) = \begin{bmatrix} \pm 1 \\ 0 \\ \pm 1 \\ 0 \end{bmatrix} \begin{matrix} \tau_1 \\ \tau_2 \\ \tau_3 \\ \tau_4 \end{matrix}$$



$$\mathcal{G} = \mathcal{T} \cup \mathcal{C}$$

indicates a path from node u to v using only edges in the spanning tree

$$T_{(\tau, c)} = \underbrace{(E_\tau^T E_\tau)^{-1} E_\tau^T}_{E_\tau^L} E(\mathcal{C})$$



\mathcal{H}_2 Performance and Effective Resistance

Consensus driven by WGN

$$\begin{cases} \dot{x}(t) &= -L(\mathcal{G})x(t) + w(t) \\ z(t) &= E(K_n)^T x(t) \end{cases} \quad \text{monitor all possible relative states}$$

$$\begin{bmatrix} x_\tau(t) \\ \bar{x}(t) \end{bmatrix} = \underbrace{\begin{bmatrix} E(\mathcal{T})^T \\ \frac{1}{n} \mathbb{1}^T \end{bmatrix}}_{S^{-1}} x(t)$$

Edge Agreement....

$$\begin{cases} \dot{x}_\tau(t) &= -L_{ess}(\mathcal{G})x_\tau(t) + E(\mathcal{T})^T w(t) \\ z(t) &= E(K_n)^T E(\mathcal{T})L_e(\mathcal{T})^{-1}x_\tau(t) \end{cases}$$



\mathcal{H}_2 Performance and Effective Resistance

Edge Agreement....

$$\Sigma_e(\mathcal{G}) \begin{cases} \dot{x}_\tau(t) & = -L_{ess}(\mathcal{G})x_\tau(t) + E(\mathcal{T})^T w(t) \\ z(t) & = E(K_n)^T E(\mathcal{T})L_e(\mathcal{T})^{-1}x_\tau(t) \end{cases}$$

$$T_{(\mathcal{T}, K_n)} = E(K_n)^T E(\mathcal{T})L_e(\mathcal{T})^{-1}$$

$$\begin{aligned} \|\Sigma_e(\mathcal{G})\|_2^2 &= \frac{1}{2} \text{tr} \left[T_{(\mathcal{T}, K_n)}^T (\mathcal{R}_{(\mathcal{T}, c)} \mathcal{R}_{(\mathcal{T}, c)}^T)^{-1} T_{(\mathcal{T}, K_n)} \right] \\ &= \frac{1}{2} R_{tot}(\mathcal{G}) \end{aligned}$$

