

Cyclically-Monotone Relations and their use in Passivity-Based Cooperative Control

Daniel Zelazo

Faculty of Aerospace Engineering

University of Groningen

16.02.2017

Duality in Cooperative Control Problems

Daniel Zelazo

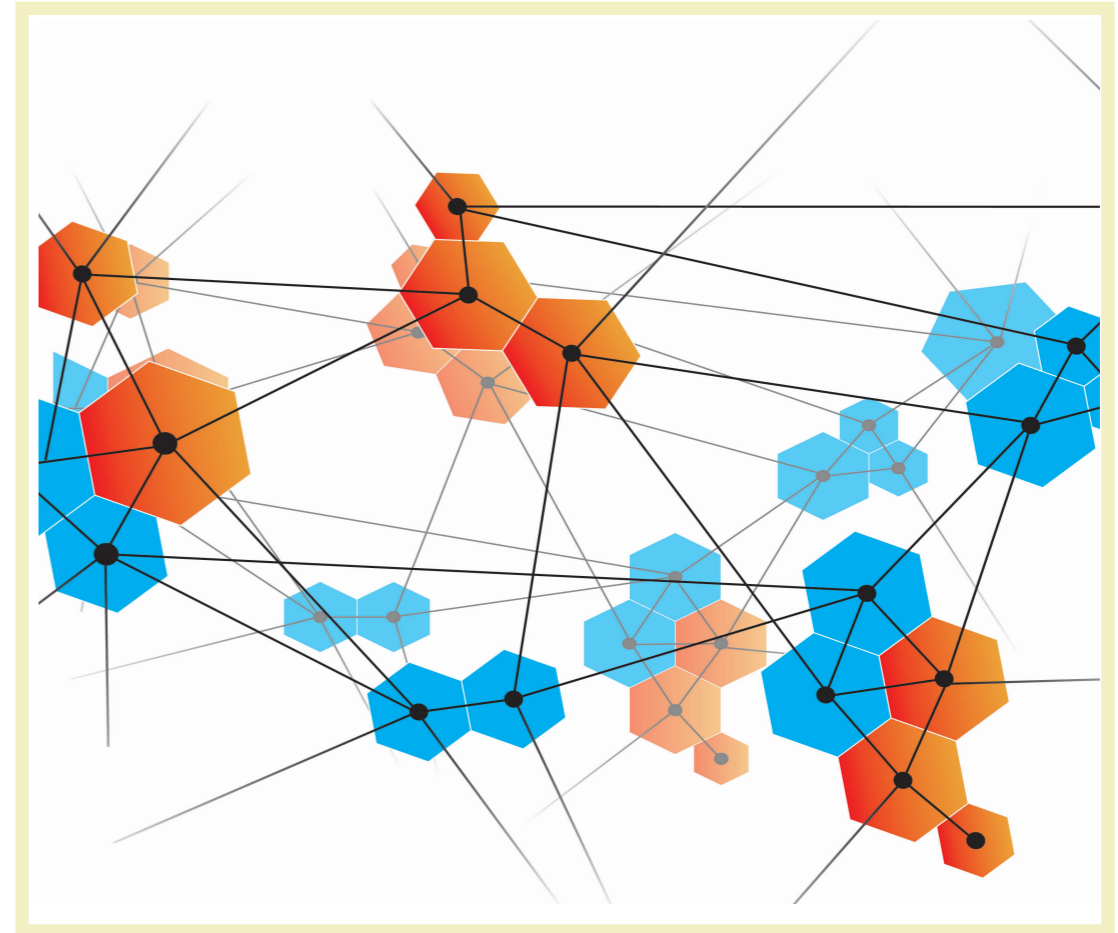
Faculty of Aerospace Engineering

University of Groningen

16.02.2017



Networked Dynamic Systems



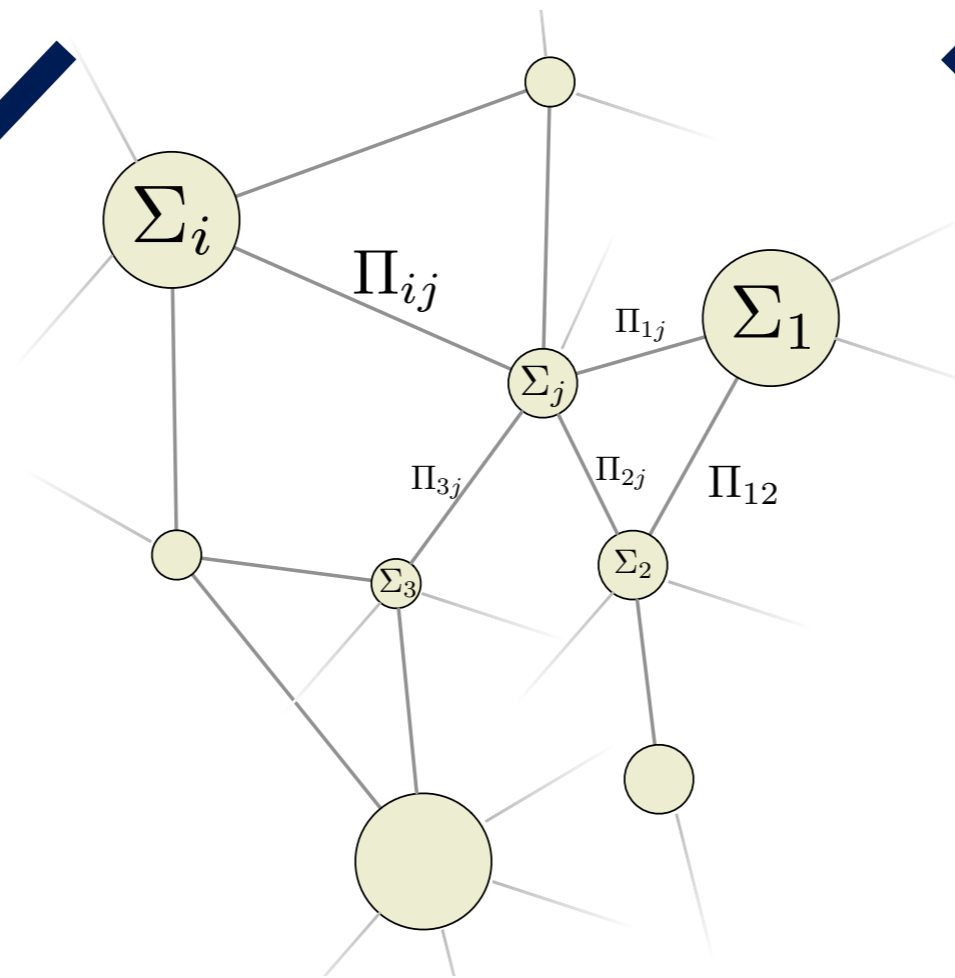
networks of dynamical systems are one of *the* enabling technologies of the future



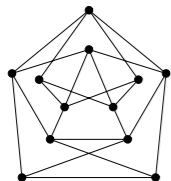
Networked Dynamic Systems

dynamics

$$\dot{x}_i(t) = f_i(x_i(t), u_i(t))$$



topology
(graph)



interaction
protocol

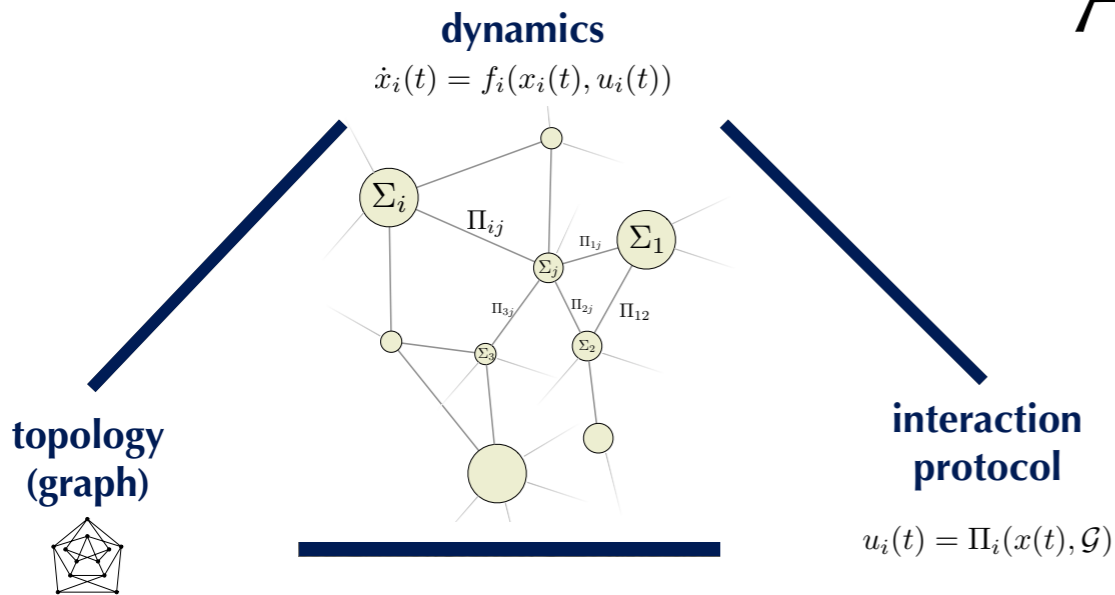
$$u_i(t) = \Pi_i(x(t), \mathcal{G})$$



Networked Dynamic Systems

Analysis

- steady-state behavior
- interplay between dynamics and graph
- equilibrium configurations



Synthesis

- design of distributed protocols
- design of “good” network structures
- robust

can we reveal *deep* results describing the underlying behavior of these systems?

in this talk...

■ Network Optimization

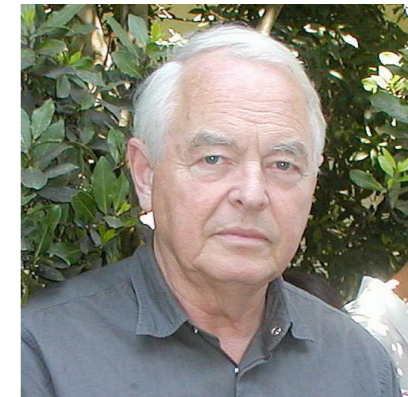
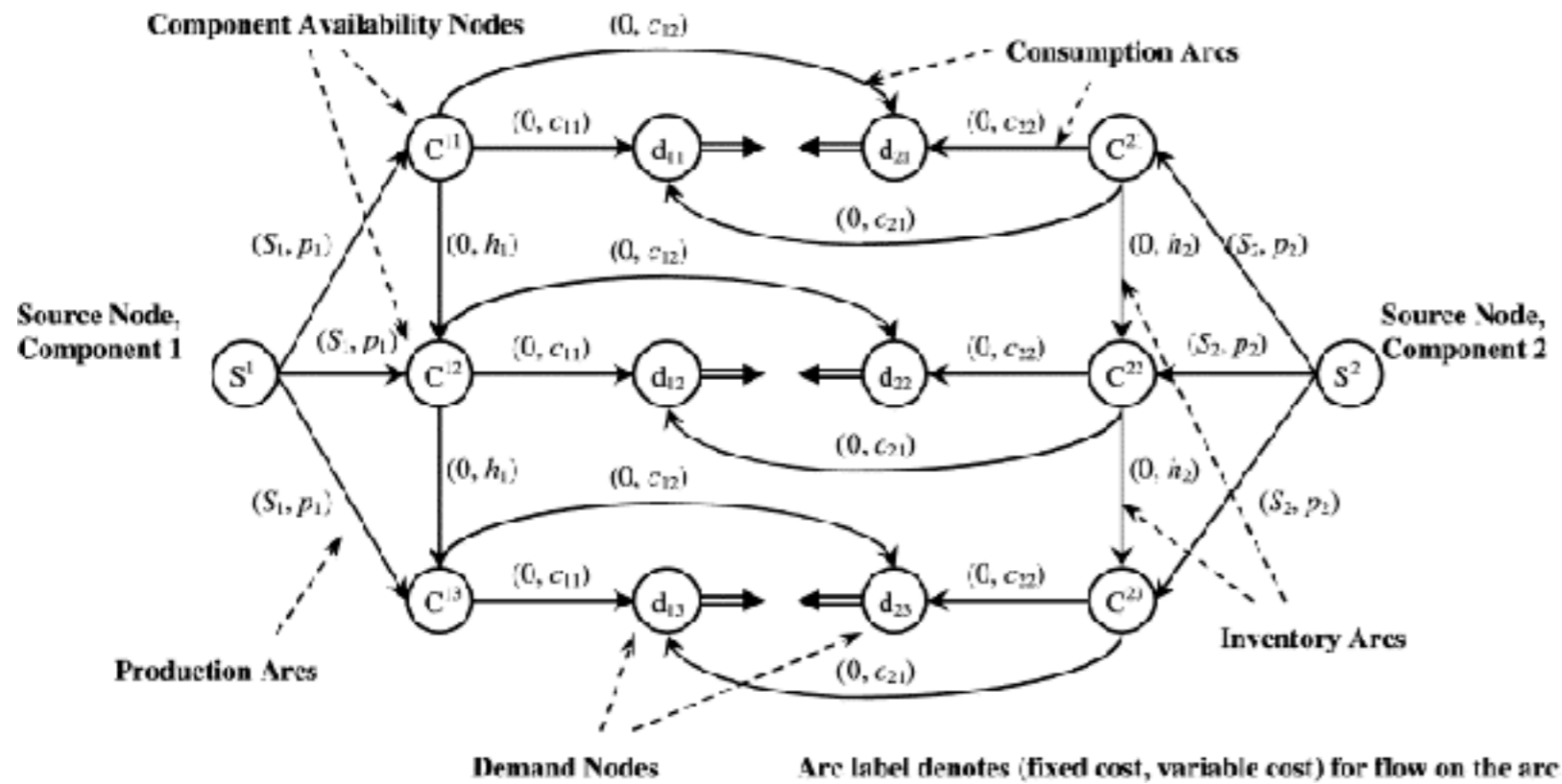
- ◆ optimal flow/optimal potential problems
- ◆ monotone/cyclically monotone relations and convex functions

■ Passivity-based Cooperative Control

- ◆ equilibrium independent passivity
- ◆ steady-state input/output maps

Duality Theory for Cooperative Control

Network Optimization



Network Flows and Monotropic Optimization

"...in fact, the great watershed in optimization isn't between linearity and nonlinearity, but convexity and nonconvexity."

R. Tyrrell Rockafellar
SIAM Review, 1993

Shortest Path Problem

Max-Flow Problem

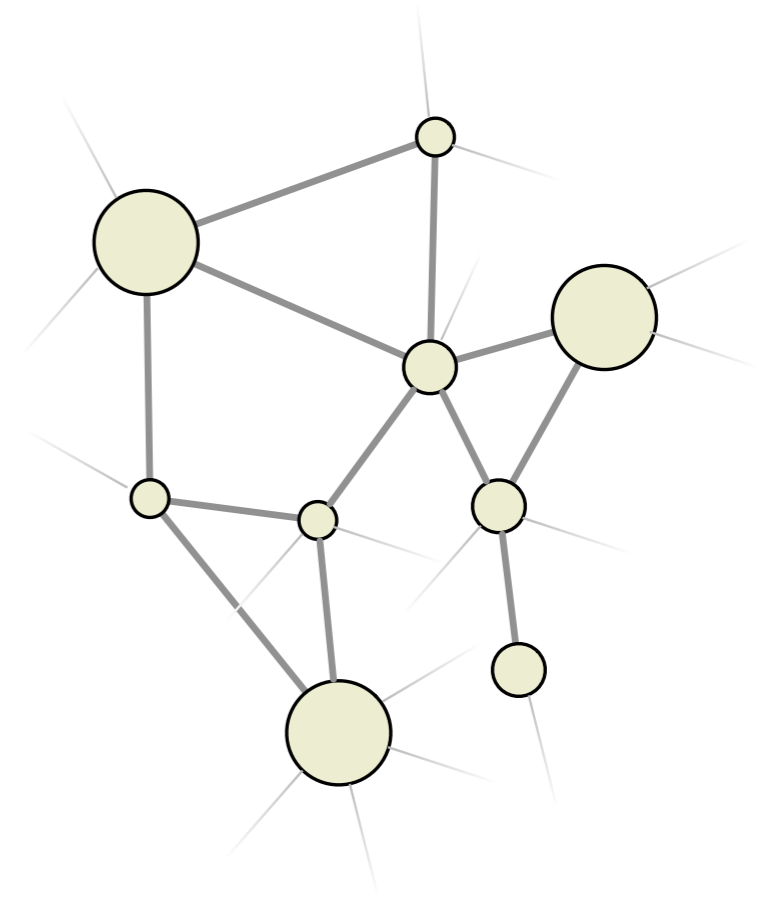
Minimum Cost Flow Problem



Network Definitions

A **network (graph)** is a mathematical structure used to model pairwise relations between objects.

$$\mathcal{G} = (\mathbf{V}, \mathbf{E})$$



Incidence Matrix

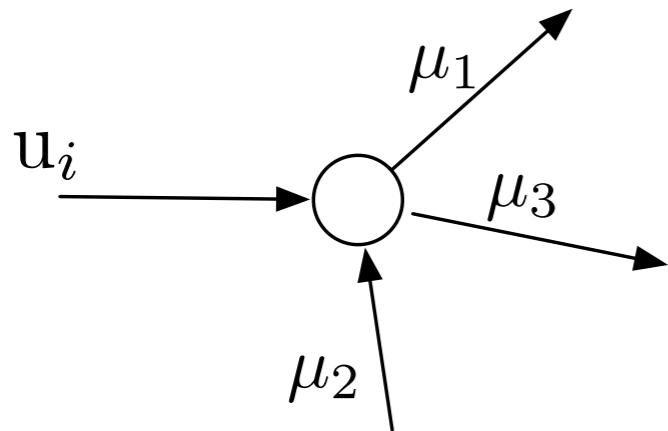
$$E(\mathcal{G}) = \mathbb{R}^{|\mathbf{V}| \times |\mathbf{E}|}$$

$$E(\mathcal{G})^T \mathbf{1} = \mathbf{0}$$

$$[E]_{ik} = \begin{cases} +1 & \text{if } i \text{ is positive end of } k \\ -1 & \text{if } i \text{ is negative end of } k \\ 0 & \text{otherwise} \end{cases}$$

Network Optimization

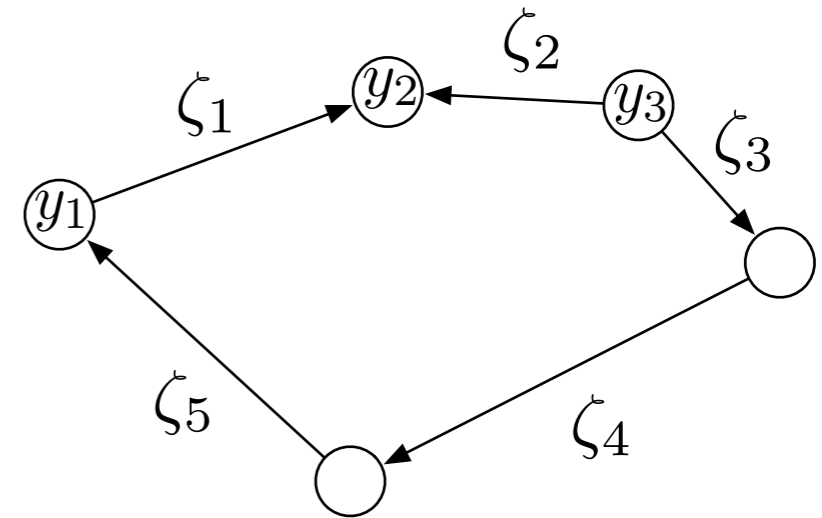
Flow “conservation” laws



$$\mathbf{u} + E(\mathcal{G})\boldsymbol{\mu} = 0$$

“flow networks”

“Cycle” laws



$$\boldsymbol{\zeta} = E^T(\mathcal{G})\mathbf{y}$$

“potential networks”

conversion formula

$$\boldsymbol{\mu}^T \boldsymbol{\zeta} = -\mathbf{y}^T \mathbf{u}.$$

Network Optimization

Optimal Flow Problem

$$\begin{aligned} \min_{\mathbf{u}, \boldsymbol{\mu}} \quad & \sum_{i=1}^{|\mathbf{V}|} C_i^{div}(\mathbf{u}_i) + \sum_{k=1}^{|\mathbf{E}|} C_k^{flux}(\boldsymbol{\mu}_k) \\ \text{s.t.} \quad & \mathbf{u} + \mathbf{E}\boldsymbol{\mu} = \mathbf{0}. \end{aligned}$$

\mathbf{u}_i : **divergence** (in/out-flow)
at a node

$\boldsymbol{\mu}_k$: **flow** on an edge

Optimal Potential Problem

$$\begin{aligned} \min_{\mathbf{y}, \boldsymbol{\zeta}} \quad & \sum_{i=1}^{|\mathbf{V}|} C_i^{pot}(\mathbf{y}_i) + \sum_{k=1}^{|\mathbf{E}|} C_k^{ten}(\boldsymbol{\zeta}_k) \\ \text{s.t.} \quad & \boldsymbol{\zeta} = \mathbf{E}^\top \mathbf{y}. \end{aligned}$$

\mathbf{y}_i : **potential** at a node

$\boldsymbol{\zeta}_k$: **tension** (potential difference)
across an edge

Dual Optimization Problems
defined over the “same” network

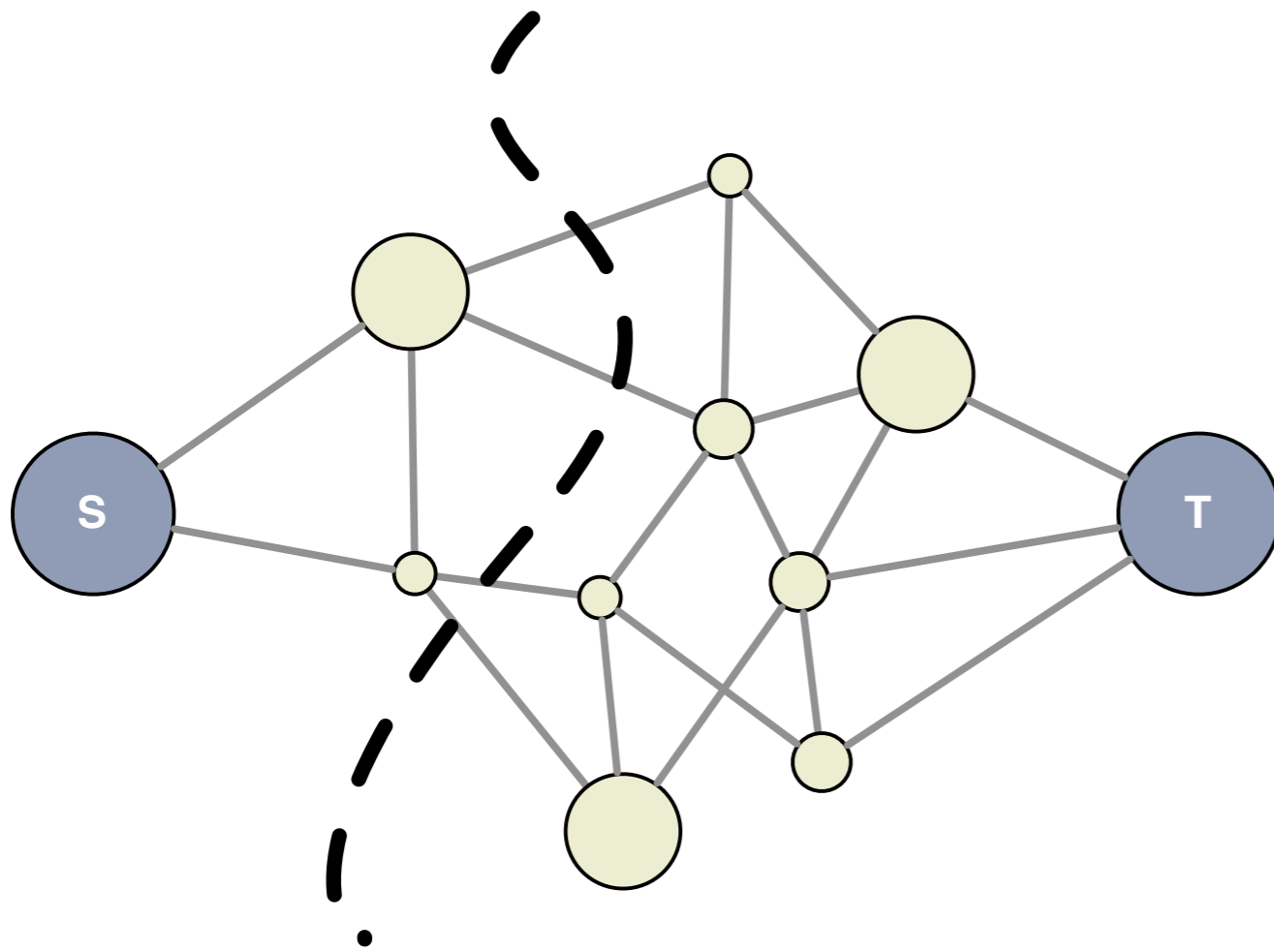
$$C_i^{pot}(\mathbf{y}_i) := C_i^{div,*} = - \inf_{\tilde{\mathbf{u}}_i} \{ C_i^{div}(\tilde{\mathbf{u}}_i) - \mathbf{y}_i \tilde{\mathbf{u}}_i \}$$



Network Optimization

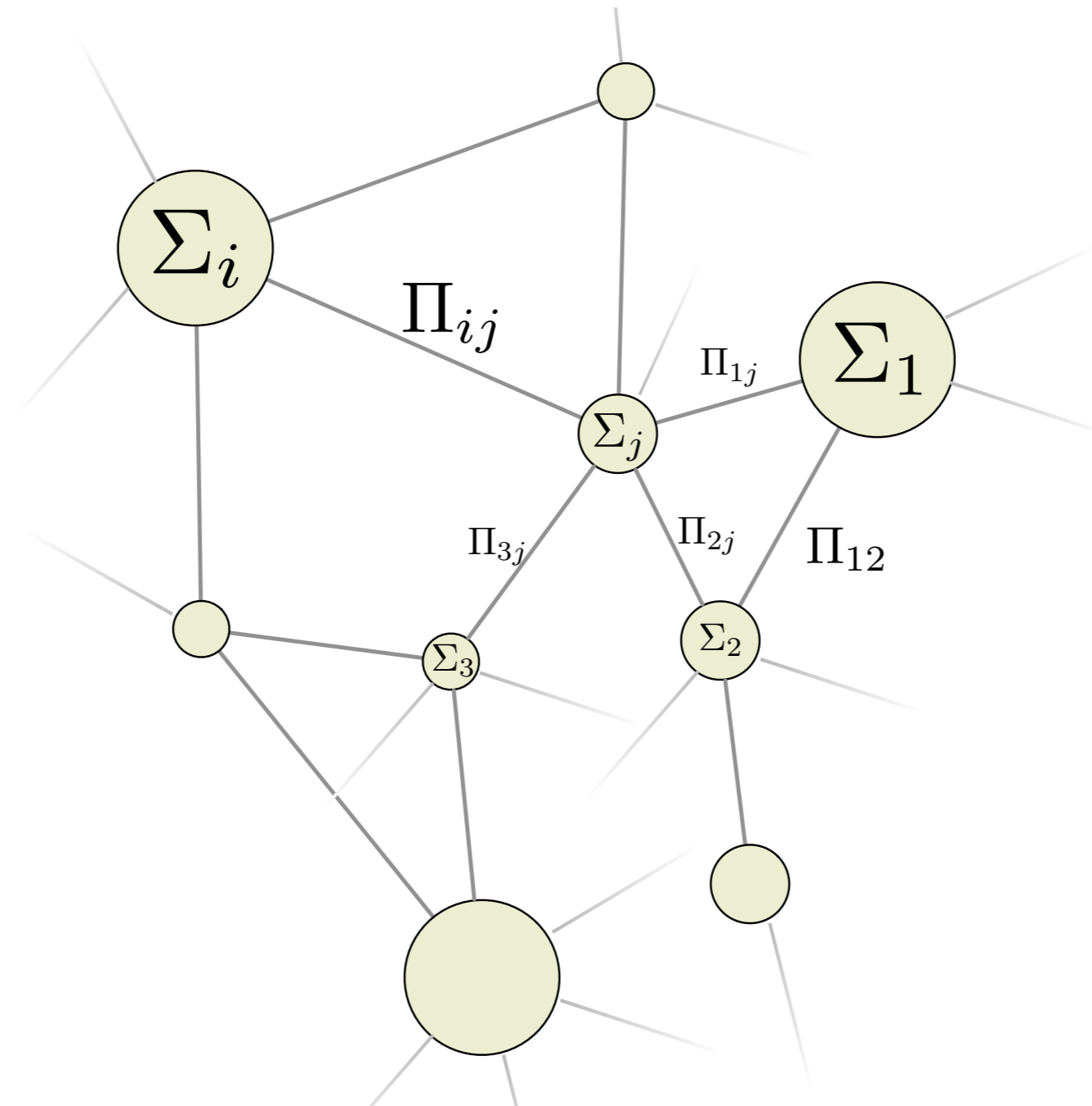
Max Flow-Min Cut Theorem

The maximum value of an S-T flow is equal to the minimum capacity over all s-t cuts.

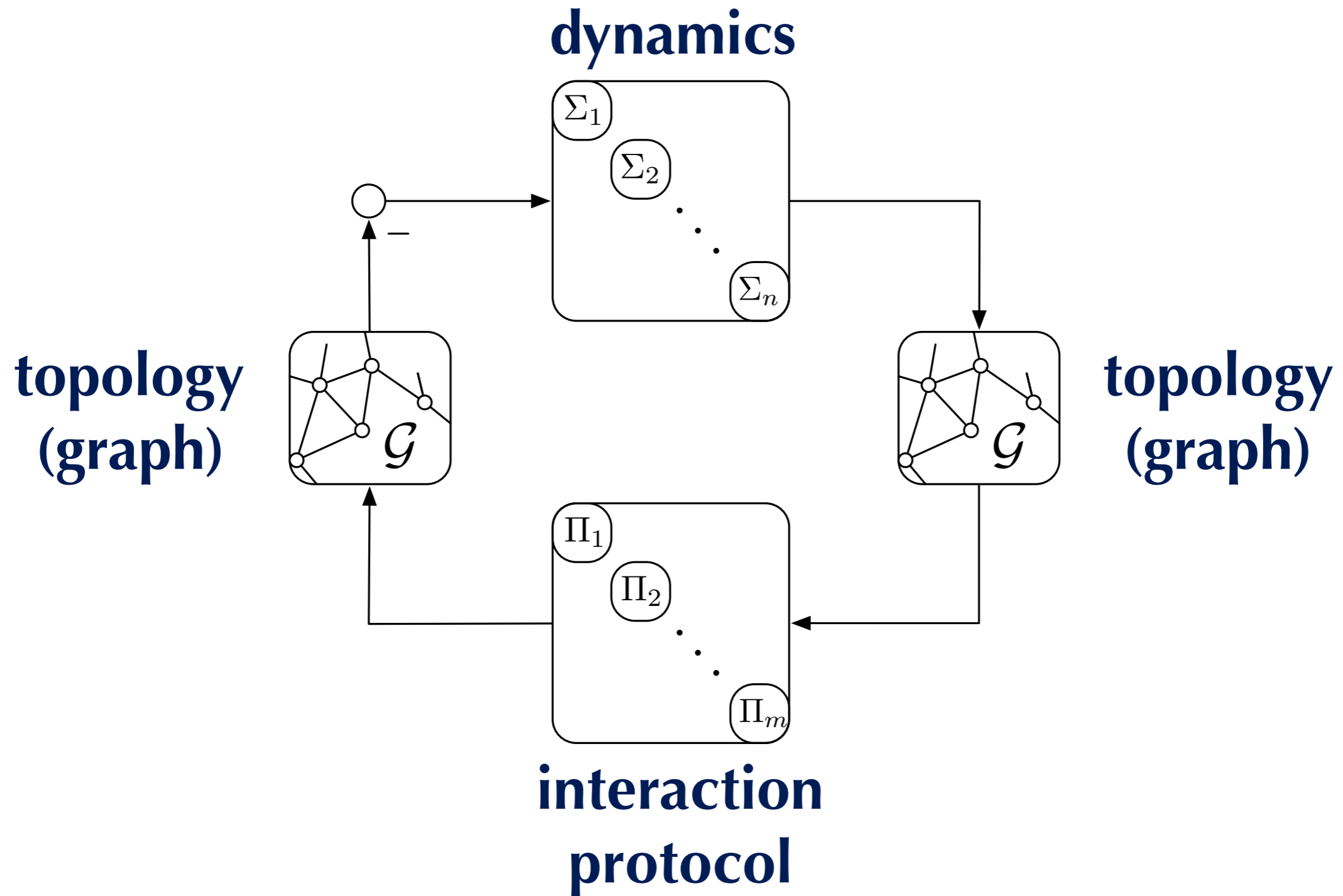


Elegant illustration of
Duality Theory

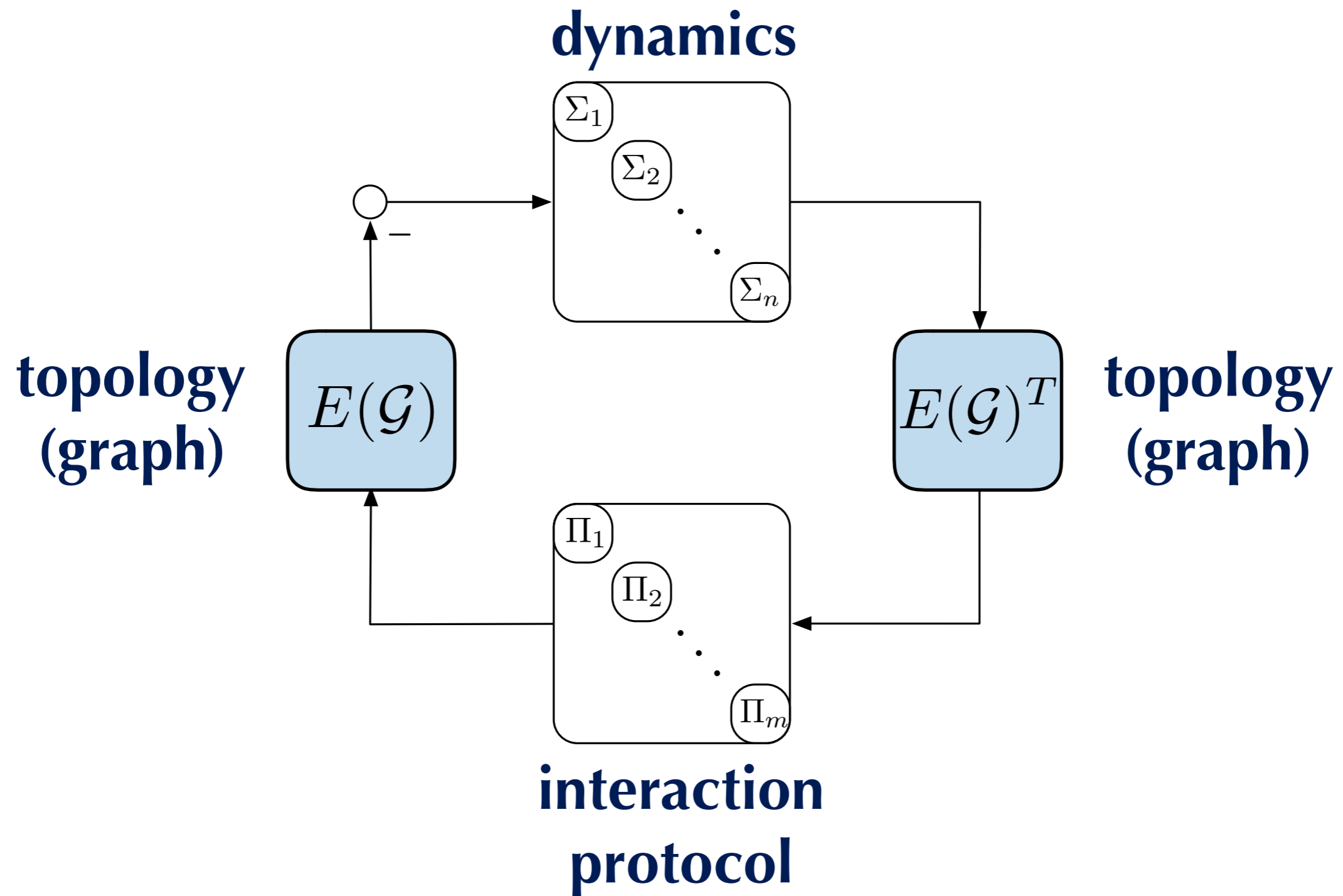
Networked Dynamic Systems



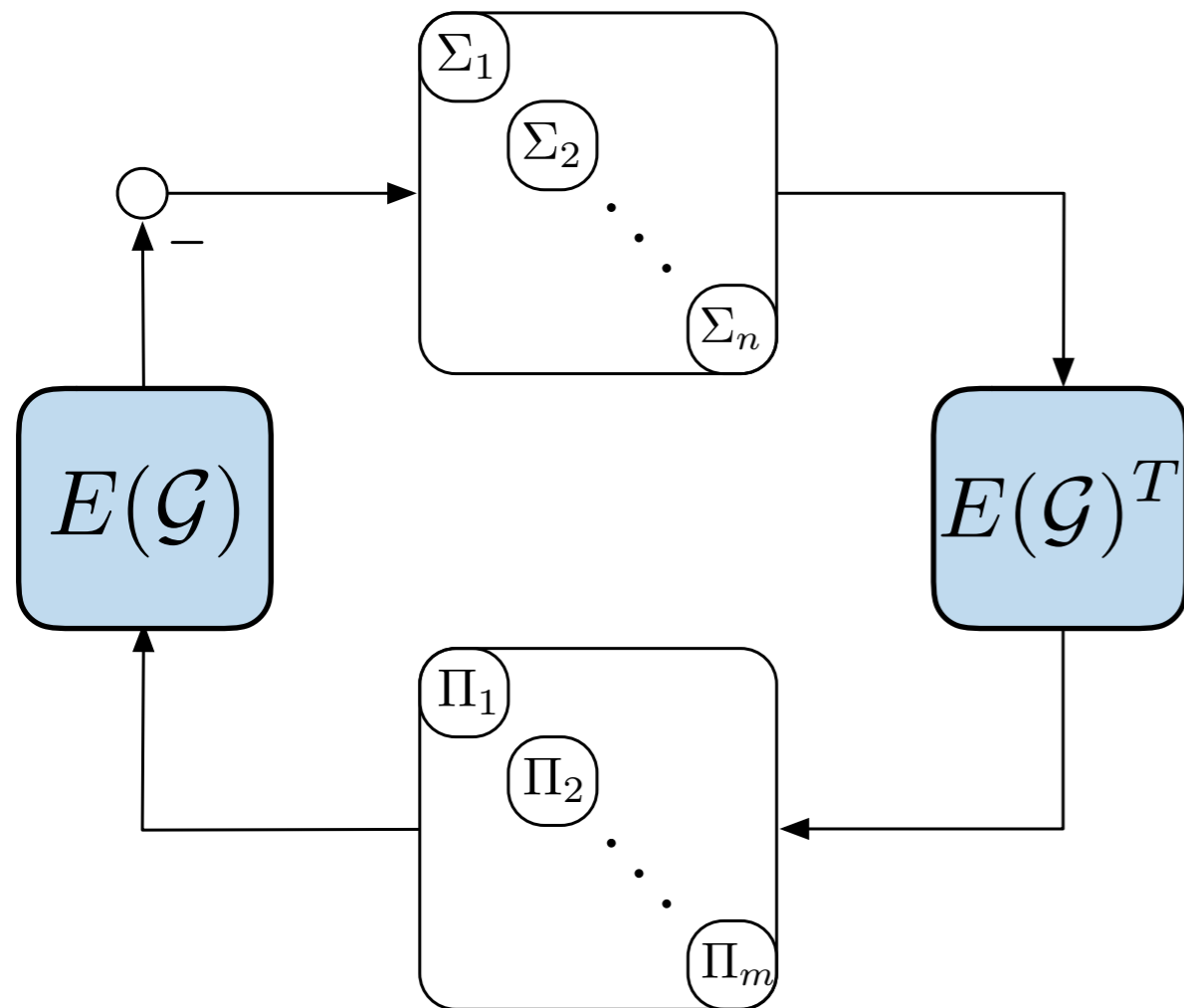
Networked Dynamic Systems



Diffusively Coupled Networks



Diffusively Coupled Networks



Kumamoto Model

$$\dot{\theta}_i = -k \sum_{i \sim j} \sin(\theta_i - \theta_j)$$

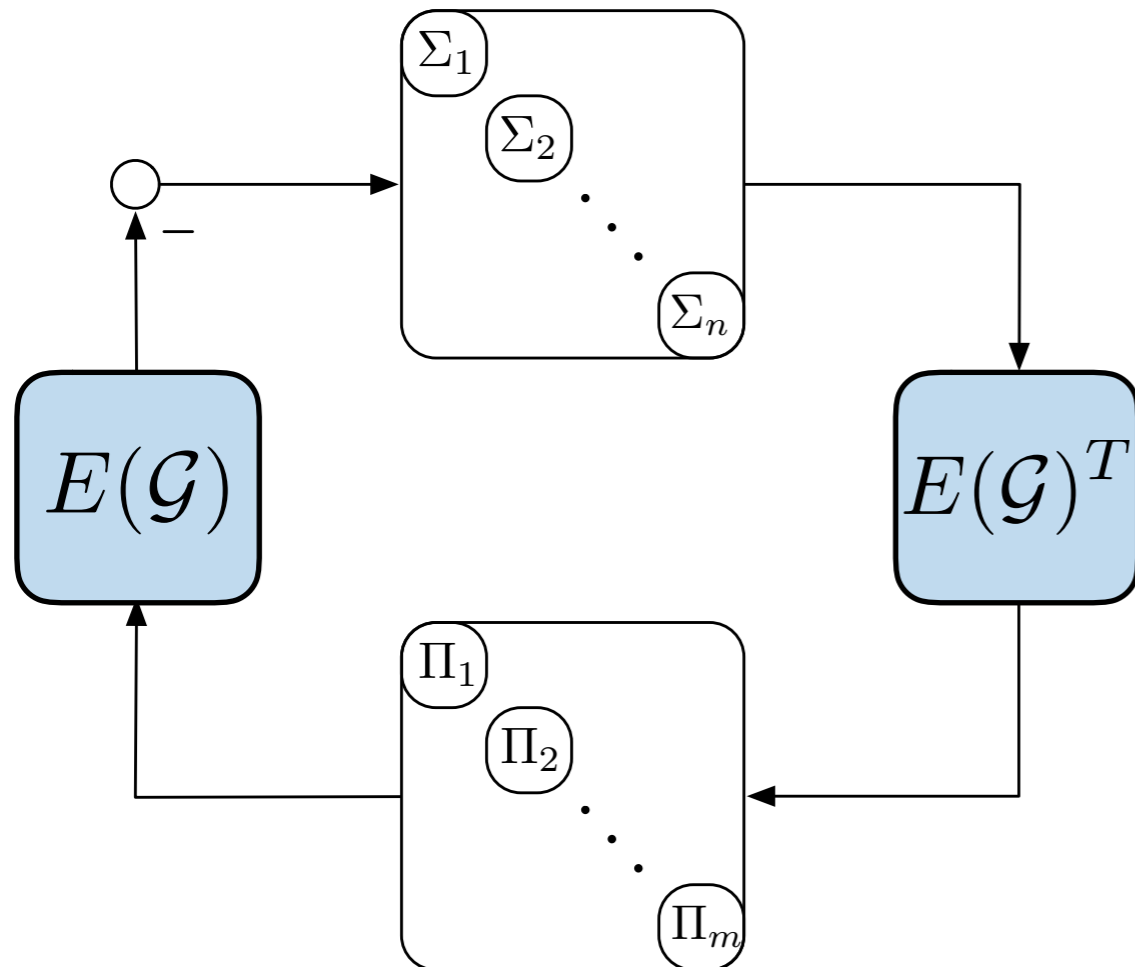
Traffic Dynamics Model

$$\dot{v}_i = \kappa_i \left(V_i^0 - v_i + V_i^1 \sum_{i \sim j} \tanh(p_j - p_i) \right)$$

Neural Network

$$\begin{aligned} C\dot{V}_i &= f(V_i, h_i) + \sum_{i \sim j} g_{ij}(V_j - V_i) \\ \dot{h}_i &= g(V_i, h_i) \end{aligned}$$

Duality and Cooperative Control



Optimal Flow Problem

$$\begin{aligned} \min_{\mathbf{u}, \boldsymbol{\mu}} \quad & \sum_{i=1}^{|\mathbf{V}|} C_i^{div}(\mathbf{u}_i) + \sum_{k=1}^{|\mathbf{E}|} C_k^{flux}(\boldsymbol{\mu}_k) \\ \text{s.t.} \quad & \mathbf{u} + E\boldsymbol{\mu} = 0. \end{aligned}$$

Optimal Potential Problem

$$\begin{aligned} \min_{\mathbf{y}, \boldsymbol{\zeta}} \quad & \sum_{i=1}^{|\mathbf{V}|} C_i^{pot}(\mathbf{y}_i) + \sum_{k=1}^{|\mathbf{E}|} C_k^{ten}(\boldsymbol{\zeta}_k) \\ \text{s.t.} \quad & \boldsymbol{\zeta} = E^T \mathbf{y}. \end{aligned}$$

The Output Agreement Problem

Plant: Dynamics on nodes

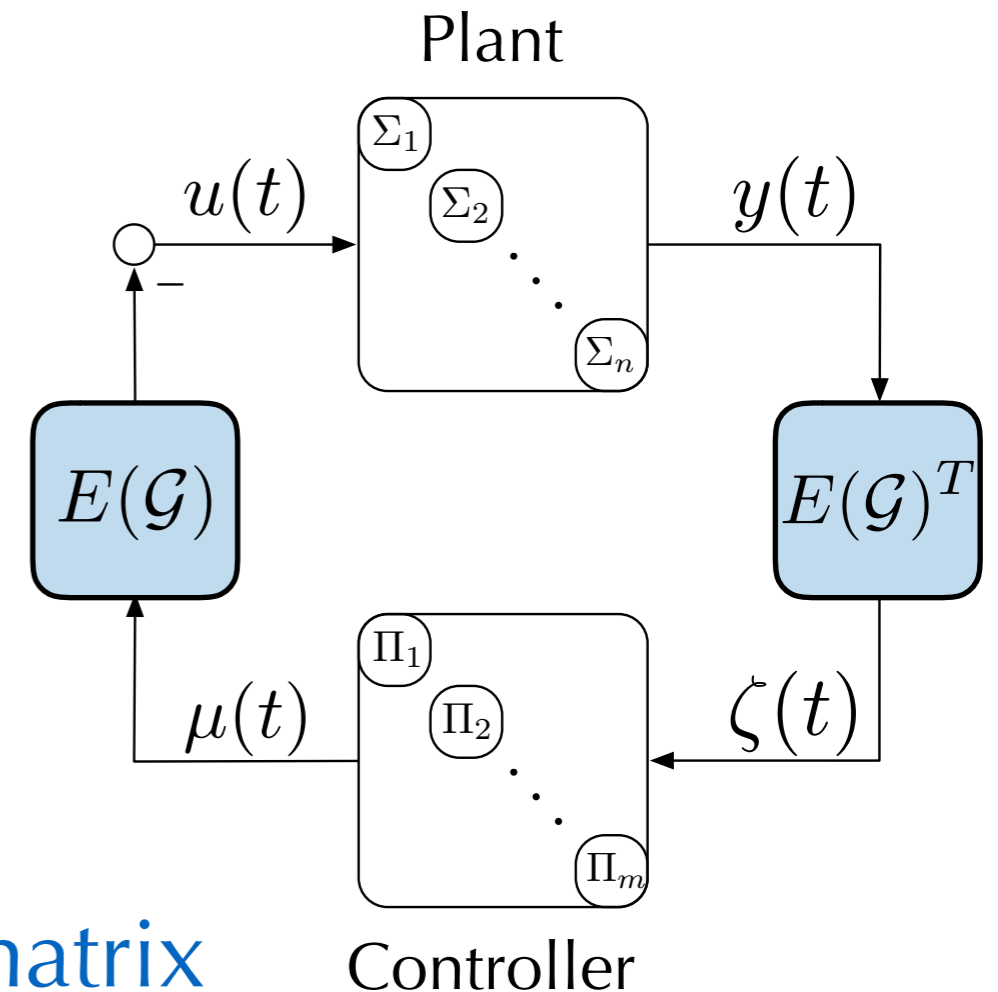
$$\Sigma_i : \quad \begin{aligned} \dot{x}_i(t) &= f_i(x_i(t), u_i(t), w_i) \\ y_i(t) &= h_i(x_i(t), u_i(t), w_i) \end{aligned}$$

Controllers: Dynamics on edges

$$\Pi_k : \quad \begin{aligned} \dot{\eta}_k(t) &= \zeta_k(t) \\ \mu_k(t) &= \psi_k(\eta_k(t), \zeta_k(t)) \end{aligned}$$

Interconnection via graph incidence matrix

$$\begin{cases} \zeta(t) = E(\mathcal{G})^T y(t) \\ u(t) = E(\mathcal{G}) \mu(t) \end{cases}$$



Control Objective

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



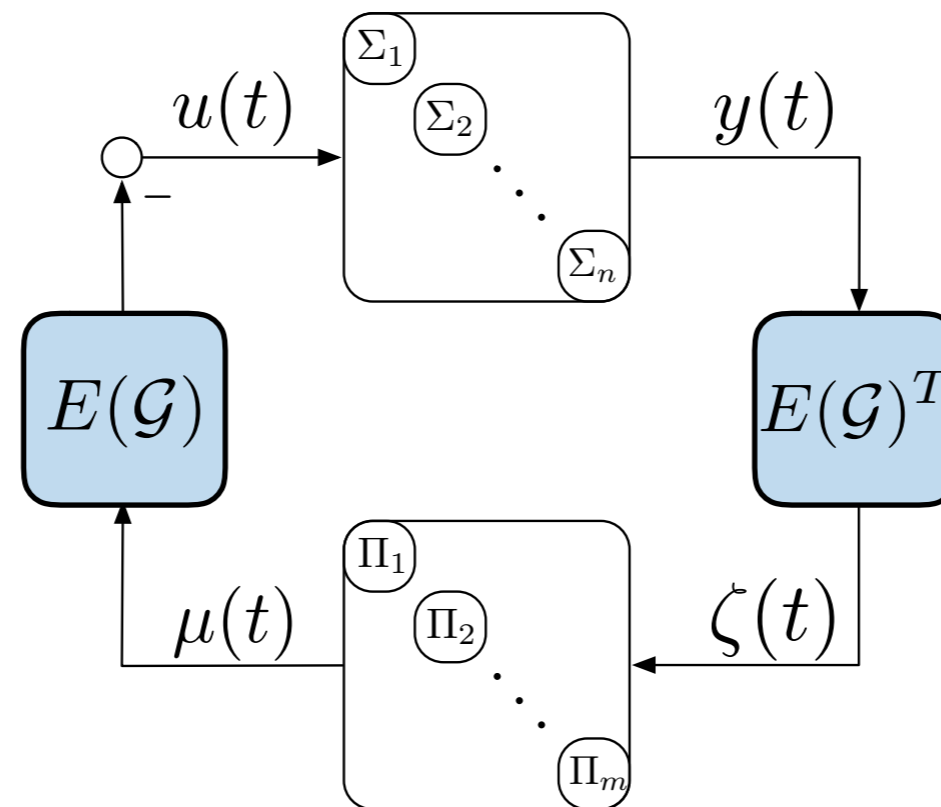
Necessary Conditions for Output Agreement

Lemma

If the networked system has a steady-state solution, \mathbf{u} , \mathbf{y} , then the solution must satisfy

$$\mathbf{u} \in \mathcal{R}(E(\mathcal{G})), \mathbf{y} \in \mathcal{N}(E^T(\mathcal{G})) = \text{span}\{\mathbf{1}\}$$

- controller must be able to generate the steady-state input \mathbf{u}



- output agreement means output of each agent is identical, i.e., $\mathbf{y} = \beta \mathbf{1}$

Passivity for Cooperative Control

a “classic” result...

- assume there exists constant signals $\mathbf{u}, \mathbf{y}, \boldsymbol{\mu}, \boldsymbol{\zeta}$ s.t. $\mathbf{u} = -E\boldsymbol{\mu}, \boldsymbol{\zeta} = E^T \mathbf{y}$
- each dynamic system is output strictly passive with respect to $\mathbf{u}_i, \mathbf{y}_i$

$$\frac{d}{dt} S_i(x_i(t)) \leq (y_i(t) - y_i)(u_i(t) - u_i) - \rho_i \|y_i(t) - y_i\|^2$$

- each controller is passive with respect to $\boldsymbol{\zeta}_k, \boldsymbol{\mu}_k$

$$\frac{d}{dt} W_k(\eta_k(t)) \leq (\mu_k(t) - \mu_k)(\zeta_k(t) - \zeta_k)$$

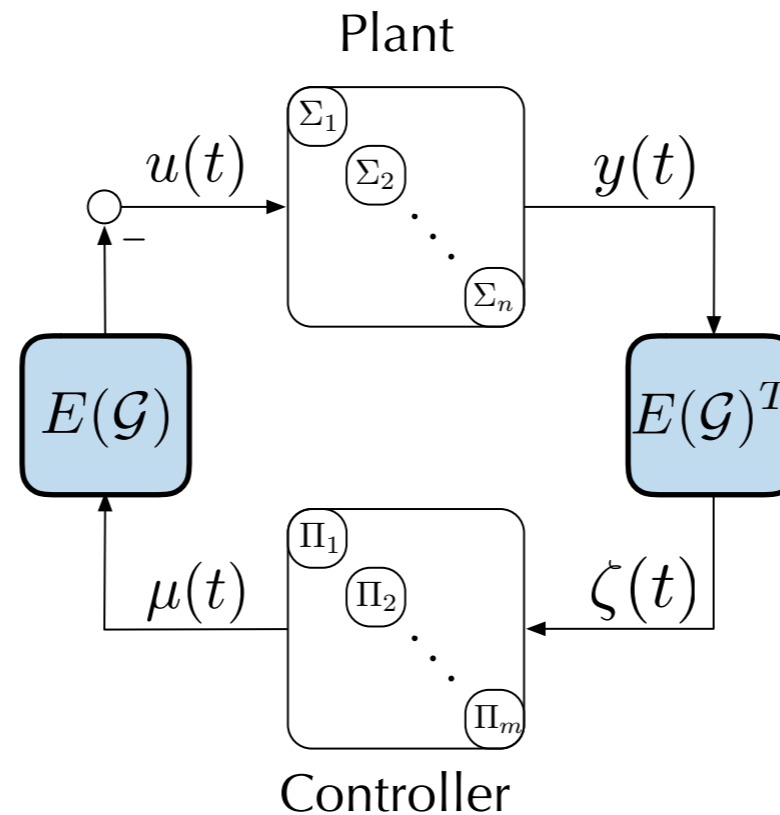
Theorem [Arcak 2007]

Suppose the above assumptions are satisfied. Then the network output converges to the constant value \mathbf{y} , i.e,

$$\lim_{t \rightarrow \infty} y(t) = \mathbf{y}$$

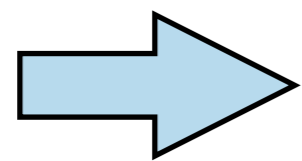


Passivity Shortcomings

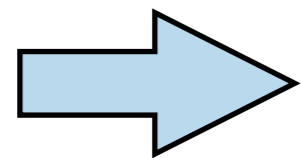


a critical assumption is the existence of constant signals

$$\mathbf{u} = -E\boldsymbol{\mu}, \quad \boldsymbol{\zeta} = E^T \mathbf{y}$$



equilibrium depends on all properties “globally”



can not be verified “locally”



Equilibrium Independent Passivity

Definition [Hines et. al. Automatica 2011]

A control system

$$\begin{aligned}\dot{x} &= f(x, u) \\ y &= h(x, u)\end{aligned}$$

is *equilibrium independent passive* (EIP) if

- i) \exists a set \mathcal{U} and function $k_x(u)$ s.t. $f(k_x(u), u) = 0 \forall u \in \mathcal{U}$
- ii) the system is passive with respect to the equilibrium input-output pair $u, y = h(k_x(u), u)$



Equilibrium Independent Passivity

Lemma [Hines et. al. Automatica 2011]

If Σ is EIP, then $k_y(u)$ is monotonically increasing.

Equilibrium input-output maps are *monotone functions!*

Equilibrium Independent Passivity

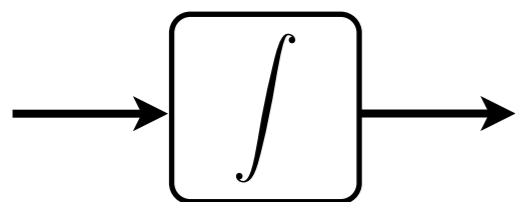
Lemma [Hines et. al. Automatica 2011]

If Σ is EIP, then $k_y(u)$ is monotonically increasing.

Equilibrium input-output maps are *monotone functions!*

but...

the integrator is *passive* w.r.t. $\mathcal{U} = \{0\}$
and any output $y \in \mathbb{R}$

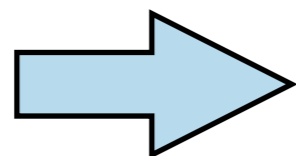


$$\dot{x}(t) = u(t)$$

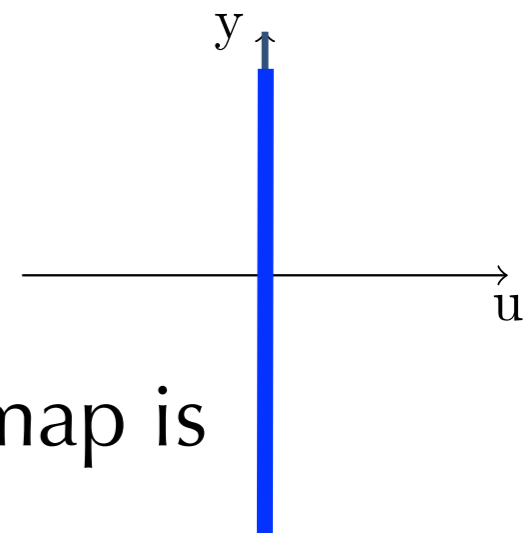
$$y(t) = x(t)$$

storage function

$$S(x(t)) = \frac{1}{2} (x(t) - y)^2$$

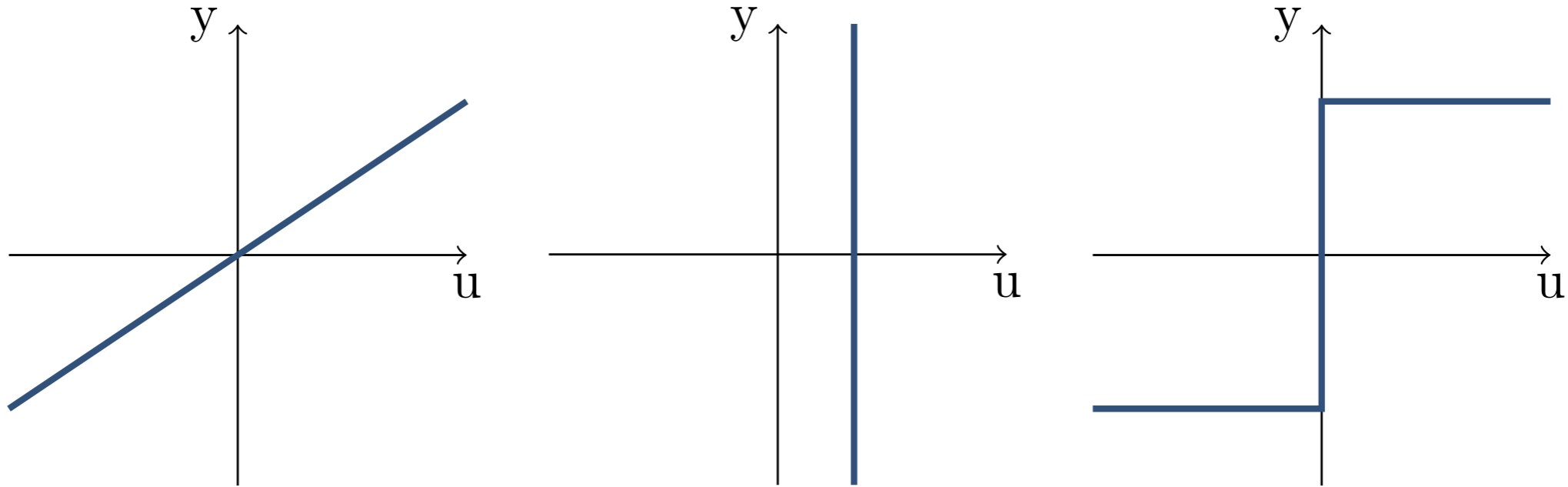


Equilibrium input-output map is
not a function!



Monotone Relations

Maximal Monotone Relations - complete non-decreasing curves in \mathbb{R}^2



a relation is *maximal monotone* if it cannot be embedded into a larger monotone relation

- k_y is maximal monotone \Leftrightarrow
- (i) for arbitrary $(u, y) \in k_y$ and $(u', y') \in k_y$
either $(u, y) \leq (u', y')$ or $(u, y) \geq (u', y')$
 - (ii) for arbitrary $(u, y) \notin k_y \exists (u', y') \in k_y$
s.t. neither $(u, y) \leq (u', y')$ nor $(u, y) \geq (u', y')$



Maximal EIP

Definition

The dynamical SISO system

$$\begin{aligned}\dot{x}(t) &= f(x(t), u(t), w) \\ y(t) &= h(x(t), u(t), w)\end{aligned}$$

is *maximal equilibrium independent passive* if there exists a maximal monotone relation $k_y \subset \mathbb{R}^2$ such that for all $(u, y) \in k_y$ there exists a positive semi-definite storage function $S(x(t))$ satisfying

$$\frac{d}{dt}S(x(t)) \leq (y(t) - y)(u(t) - u).$$

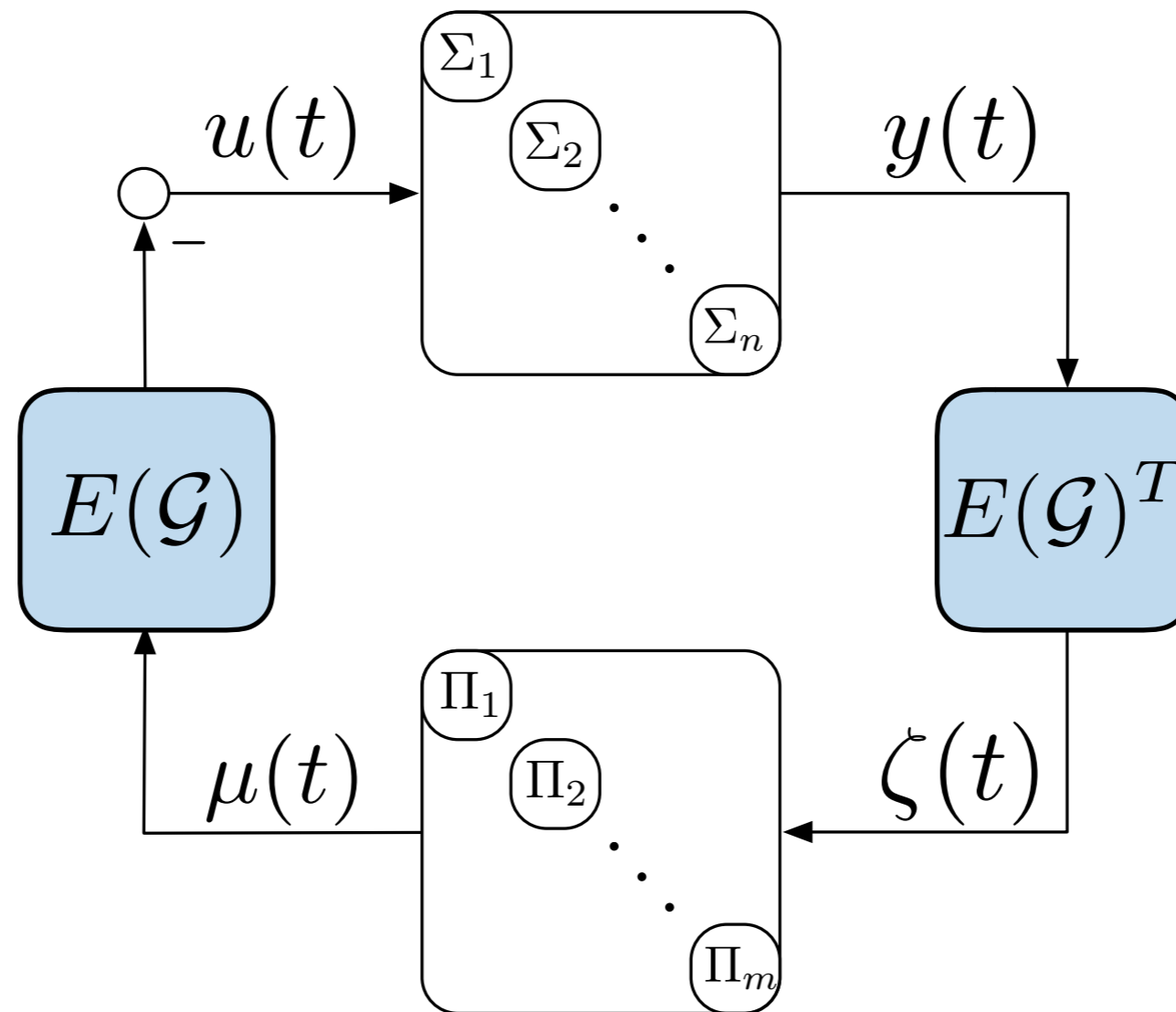
Furthermore, it is *output-strictly maximal equilibrium independent passive* if additionally there is a constant $\rho > 0$ such that

$$\frac{d}{dt}S(x(t)) \leq (y(t) - y)(u(t) - u) - \rho \|y(t) - y\|^2.$$



Maximal EIP

output strictly maximal EIP



maximal EIP

Necessary Conditions (revisited)

Lemma

If the networked system has a steady-state solution, \mathbf{u} , \mathbf{y} , then the solution must satisfy

$$\mathbf{u} \in \mathcal{R}(E(\mathcal{G})), \mathbf{y} \in \mathcal{N}(E^T(\mathcal{G})) = \text{span}\{\mathbf{1}\}$$

and

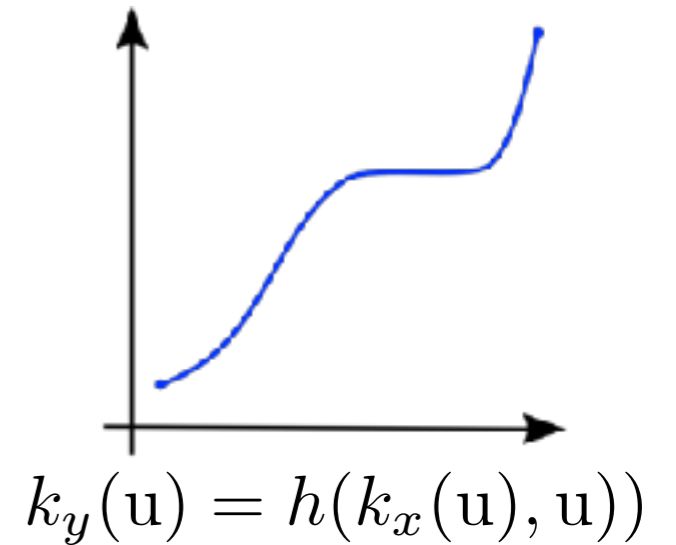
$$\mathbf{y} \in k_y(\mathbf{u})$$

A “network feasibility problem”

Monotone Relations and Convex Functions

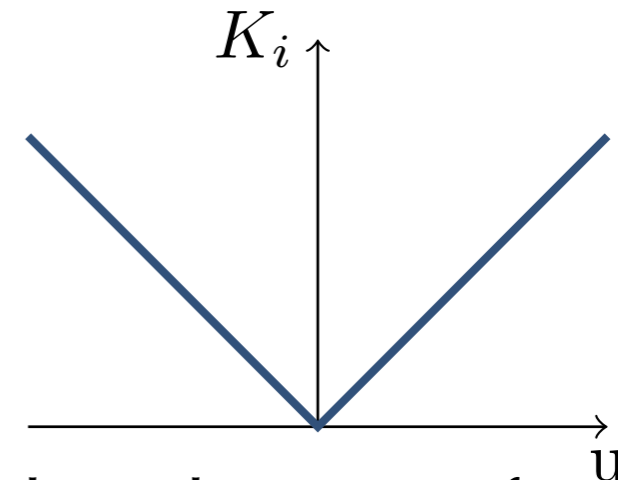
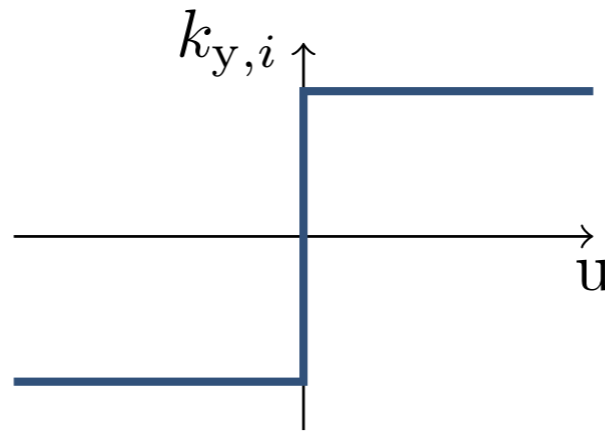
Theorem [Rockafellar, Convex Analysis]

The sub-differential for the closed proper convex functions on \mathbb{R} are the maximal monotone relations from \mathbb{R} to \mathbb{R} .



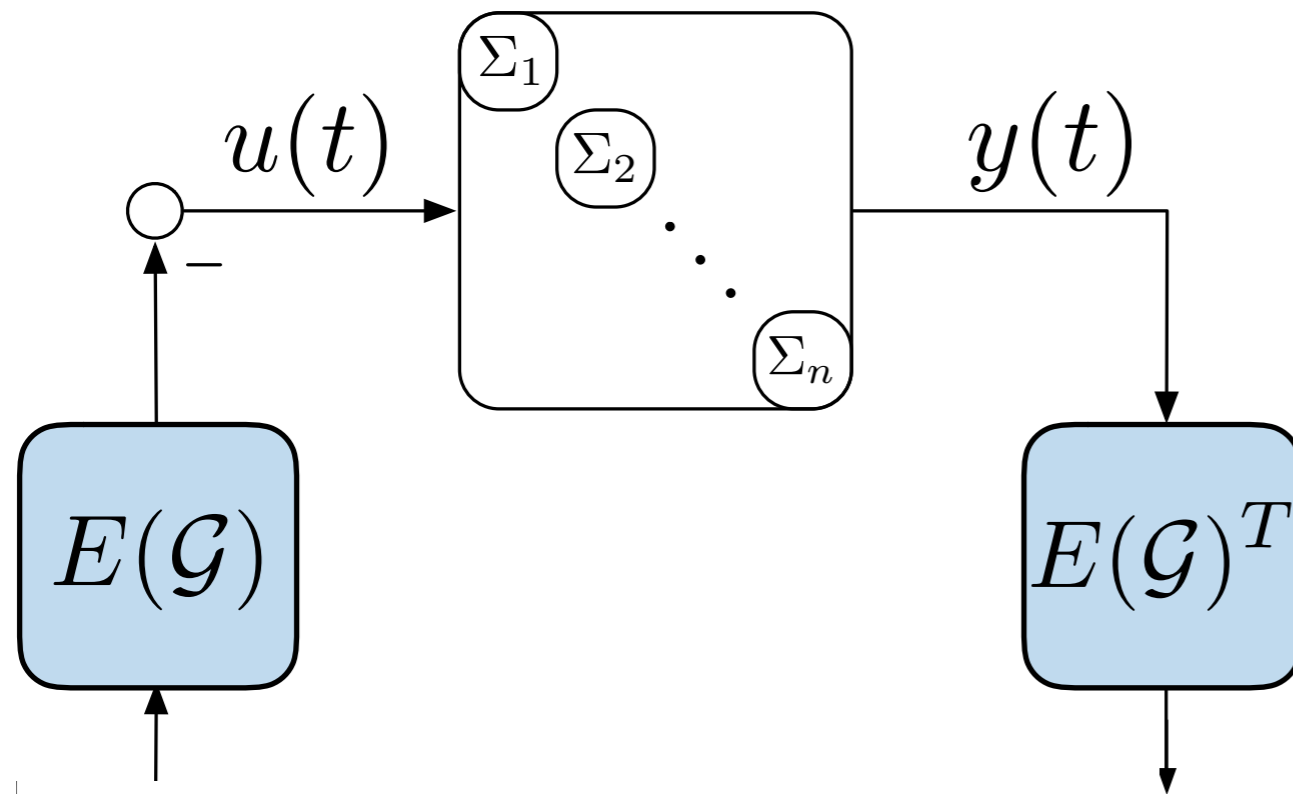
integral function of equilibrium i/o map

$$\partial K_i(u_i) = k_{y,i}(u_i)$$



proper, closed convex function

Duality in Cooperative Control



- * Suppose systems are output strictly maximal EIP
- * Equilibrium Input-Output Map

$$k_y \subset \mathbb{R} \times \mathbb{R}$$

$$y \in k_y(u)$$

$$\mathbf{u} \in \mathcal{R}(E(\mathcal{G})), \mathbf{y} \in \mathcal{N}(E^T(\mathcal{G})) = \text{span}\{\mathbf{1}\}$$

$$\mathbf{u}^T \mathbf{y} = 0$$

integral function of Equilibrium I/O
Maps are *Convex!*

$$\partial K_i(u_i) = k_{y,i}(u_i)$$



Duality in Cooperative Control

Optimal Flow Problem

$$\begin{aligned} & \text{(OFP1)} \\ \min_{\mathbf{u}, \boldsymbol{\mu}} & \sum_{i=1}^{|\mathbf{V}|} K_i(\mathbf{u}_i) \quad (= \mathbf{K}(\mathbf{u})) \\ \text{s.t.} & \quad \mathbf{u} + E\boldsymbol{\mu} = 0. \end{aligned}$$

Optimal Potential Problem

$$\begin{aligned} & \text{(OPP1)} \\ \min_{\mathbf{y}_i} & \sum_{i=1}^{|\mathbf{V}|} K_i^*(\mathbf{y}_i) \quad (= \mathbf{K}^*(\mathbf{y})) \\ \text{s.t.} & \quad E^\top \mathbf{y} = 0. \end{aligned}$$

$$K_i^*(\mathbf{y}_i) = \sup_{\mathbf{u}_i} \{ \mathbf{y}_i \mathbf{u}_i - K_i(\mathbf{u}_i) \}$$



Duality in Cooperative Control

Optimal Flow Problem

$$\begin{aligned} & \text{(OFP1)} \\ & \min_{\mathbf{u}, \boldsymbol{\mu}} \sum_{i=1}^{|\mathcal{V}|} K_i(\mathbf{u}_i) \\ & \text{s.t. } \mathbf{u} + E\boldsymbol{\mu} = 0. \end{aligned}$$

Optimal Potential Problem

$$\begin{aligned} & \text{(OPP1)} \\ & \min_{\mathbf{y}_i} \sum_{i=1}^{|\mathcal{V}|} K_i^*(\mathbf{y}_i) \\ & \text{s.t. } E^\top \mathbf{y} = 0. \end{aligned}$$

Theorem

Assume all the node dynamics are maximal EIP. If the networked system has a steady-state solution \mathbf{u}, \mathbf{y} , then

- 1) \mathbf{u} is an optimal solution of OFP1,
- 2) \mathbf{y} is an optimal solution to OPP1,
- 3) $\sum_{i=1}^{|\mathcal{V}|} K_i(\mathbf{u}_i) + \sum_{i=1}^{|\mathcal{V}|} K_i^*(\mathbf{y}_i) = 0$



Duality in Cooperative Control

Optimal Flow Problem

$$\begin{aligned} & \text{(OFP1)} \\ & \min_{\mathbf{u}, \boldsymbol{\mu}} \sum_{i=1}^{|\mathbf{V}|} K_i(\mathbf{u}_i) \\ & \text{s.t. } \mathbf{u} + E\boldsymbol{\mu} = 0. \end{aligned}$$

Optimal Potential Problem

$$\begin{aligned} & \text{(OPP1)} \\ & \min_{\mathbf{y}_i} \sum_{i=1}^{|\mathbf{V}|} K_i^*(\mathbf{y}_i) \\ & \text{s.t. } E^\top \mathbf{y} = 0. \end{aligned}$$

$\partial K_i(\mathbf{u}_i) = k_{\mathbf{y},i}(\mathbf{u}_i)$ maximal (strongly) monotone relations

\Rightarrow OFP1 is feasible and strictly convex

\Rightarrow by strong duality, only one solution to OPP1 exists

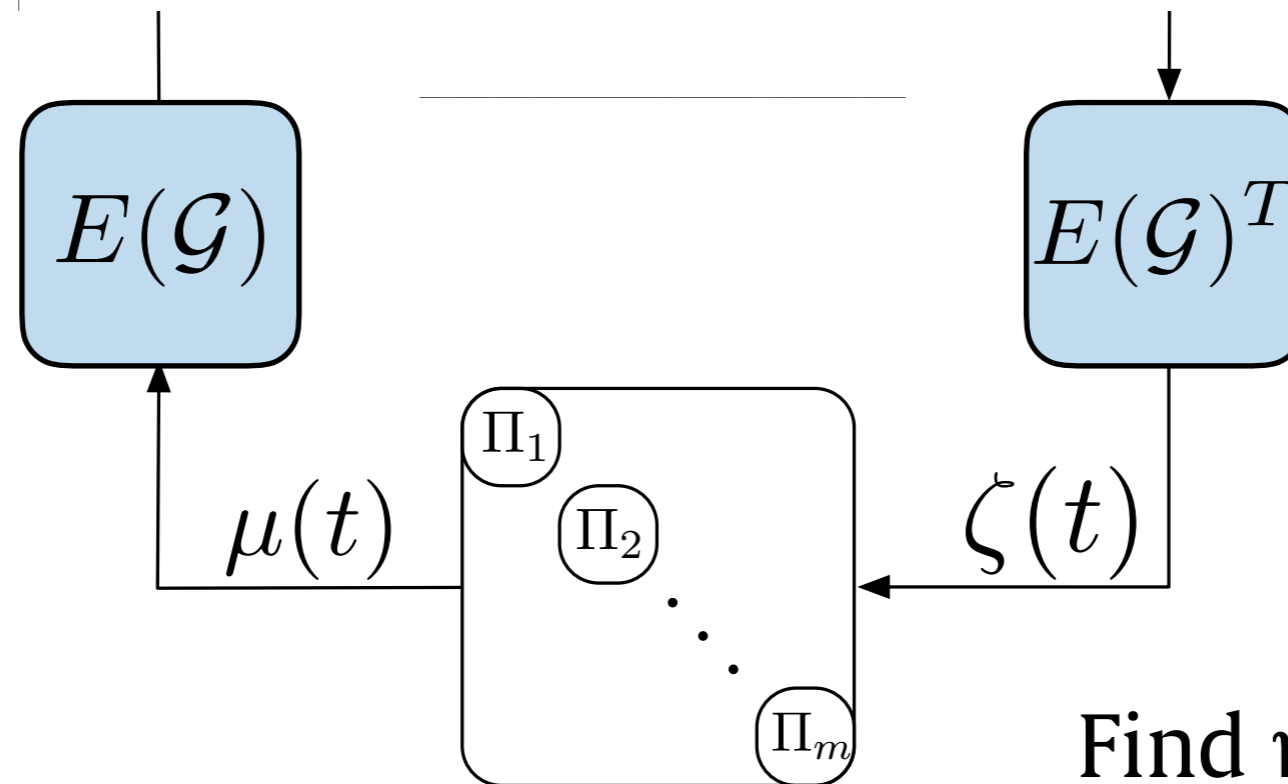
\Rightarrow exactly one output agreement solution exists



Duality in Cooperative Control

How do the controls generate the correct inputs?

$$\Pi_k : \begin{aligned} \dot{\eta}_k(t) &= \zeta_k(t) \\ \mu_k(t) &= \psi_k(\eta_k(t), \zeta_k(t)) \end{aligned}$$

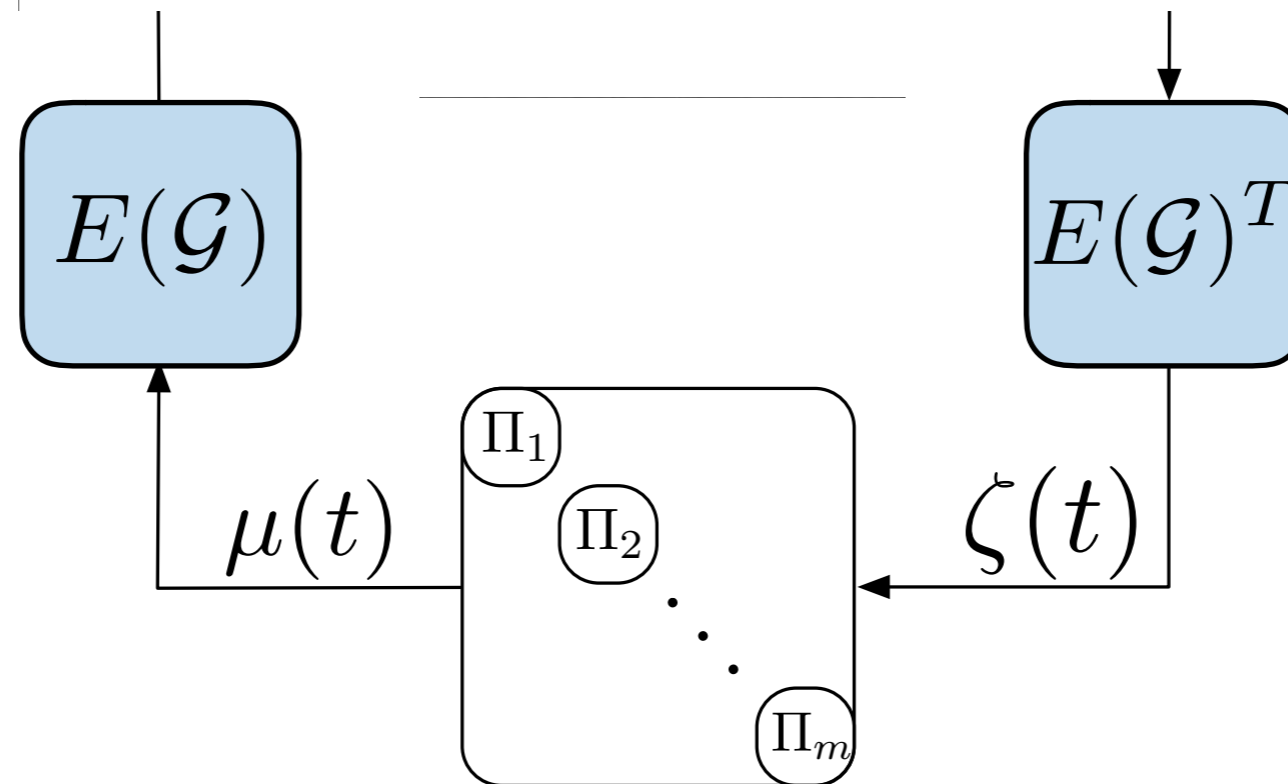


$$\begin{aligned} \text{Find } \eta &\in \mathcal{R}(E^T) \\ \text{s.t. } \mathbf{u} &= -E\psi(\eta). \end{aligned}$$

Duality in Cooperative Control

How do the controls generate the correct inputs?

$$\Pi_k : \begin{aligned} \dot{\eta}_k(t) &= \zeta_k(t) \\ \mu_k(t) &= \psi_k(\eta_k(t), \zeta_k(t)) \end{aligned} \quad \text{assume strongly monotone}$$



Let $P_k(\eta)$ be such that $\nabla P_k = \psi_k$.

Duality in Cooperative Control

Optimal Potential Problem

(OPP2)

$$\begin{aligned} \min_{\eta, \mathbf{v}} \quad & \sum_{k=1}^{|\mathbf{E}|} P_k(\eta_k) + \sum_{i=1}^{|\mathbf{V}|} \mathbf{u}_i \mathbf{v}_i \\ \text{s.t.} \quad & \eta = E^\top \mathbf{v}. \end{aligned}$$

Optimal Flow Problem

(OFP2)

$$\begin{aligned} \min_{\mu} \quad & \sum_{k=1}^{|\mathbf{E}|} P_k^*(\mu_k) \\ \text{s.t.} \quad & \mathbf{u} + E\mu = 0, \end{aligned}$$

Theorem

Assume all the node dynamics are maximal EIP. and the controller dynamics are such that all output maps ψ_k are strongly monotone and define P_k such that $\nabla P_k(\eta_k) = \psi_k(\eta_k)$. Then the networked system has an output agreement steady-state solution. Furthermore, let η be the state-state of the controller in output agreement, then

- 1) η is an optimal solution of OPP2,
- 2) $\mu = \psi(\eta)$ is an optimal solution to OFP2,
- 3) $\sum_{k=1}^{|\mathcal{E}|} P_k^*(\mu_k) + \sum_{k=1}^{|\mathcal{E}|} P_k(\eta_k) = \mu^\top \eta$



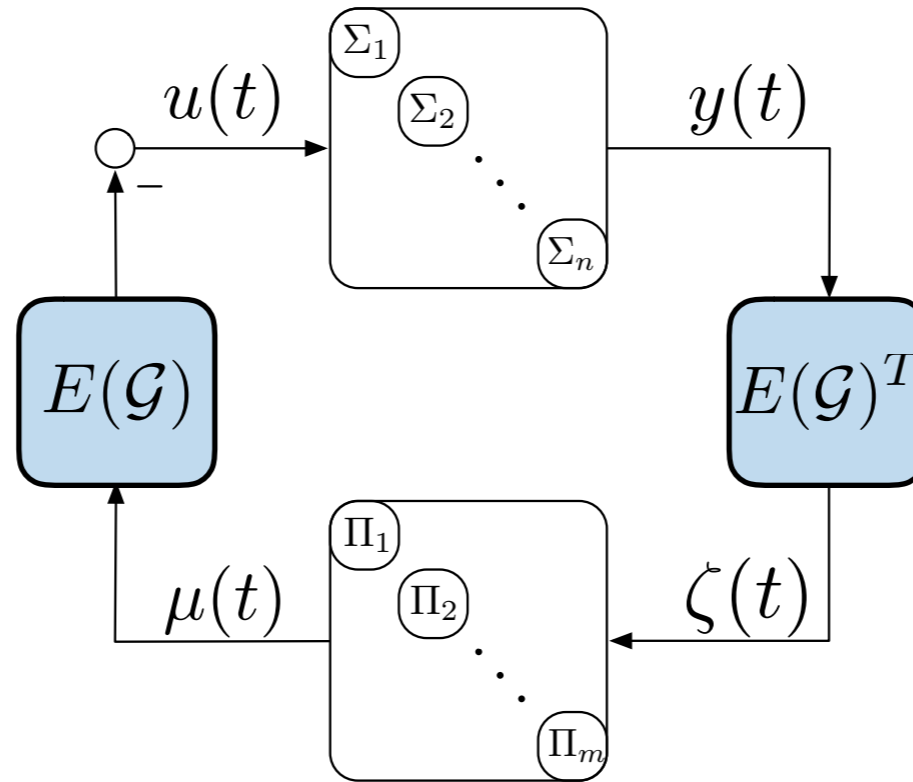
The Closed Loop

$$\min_{\mathbf{u}, \boldsymbol{\mu}} \sum_{i=1}^{|\mathbf{V}|} K_i(\mathbf{u}_i)$$

$$\text{s.t. } \mathbf{u} + E\boldsymbol{\mu} = 0.$$

$$\min_{\mathbf{y}_i} \sum_{i=1}^{|\mathbf{V}|} K_i^*(\mathbf{y}_i),$$

$$\text{s.t. } E^T \mathbf{y} = 0.$$



$$\mathbf{y} = \partial \mathbf{K}(\mathbf{u})$$

Divergence \mathbf{u} ————— Potential \mathbf{y}

$$\mathbf{u} = -E\boldsymbol{\mu}$$

$$\boldsymbol{\zeta} = E^T \mathbf{y}$$

Flow $\boldsymbol{\mu}$ ————— Tension $\boldsymbol{\eta}$

Tension $\boldsymbol{\zeta}$

$$\boldsymbol{\mu} = \nabla \mathbf{P}(\boldsymbol{\eta})$$

$$\min_{\boldsymbol{\mu}} \sum_{k=1}^{|\mathbf{E}|} P_k^*(\boldsymbol{\mu}_k)$$

$$\text{s.t. } \mathbf{u} + E\boldsymbol{\mu} = 0,$$

$$\min_{\boldsymbol{\eta}, \mathbf{v}} \sum_{k=1}^{|\mathbf{E}|} P_k(\boldsymbol{\eta}_k) - \sum_{i=1}^{|\mathbf{V}|} \mathbf{u}_i \mathbf{v}_i,$$

$$\text{s.t. } \boldsymbol{\eta} = E^T \mathbf{v}.$$



From SISO to MIMO - Cyclic Monotonicity

Definition

Consider $R \subset \mathbb{R}^n \times \mathbb{R}^n$. The relation R is *Cyclicly Monotone* if for any $N \geq 1$ and any pairs $(u_i, y_i) \in R, i = 1, \dots, N$,

$$\sum_{i=1}^N y_i^T (u_i - u_{i-1}) \geq 0.$$

Theorem [Rockafellar, 1966]

A relation $R \subset \mathbb{R}^n \times \mathbb{R}^n$ is cyclicly monotone if and only if it is contained in the subgradient of a convex function $\psi : \mathbb{R}^n \rightarrow \mathbb{R}$.



An Example - Vehicle Platooning



Microscopic Traffic Model

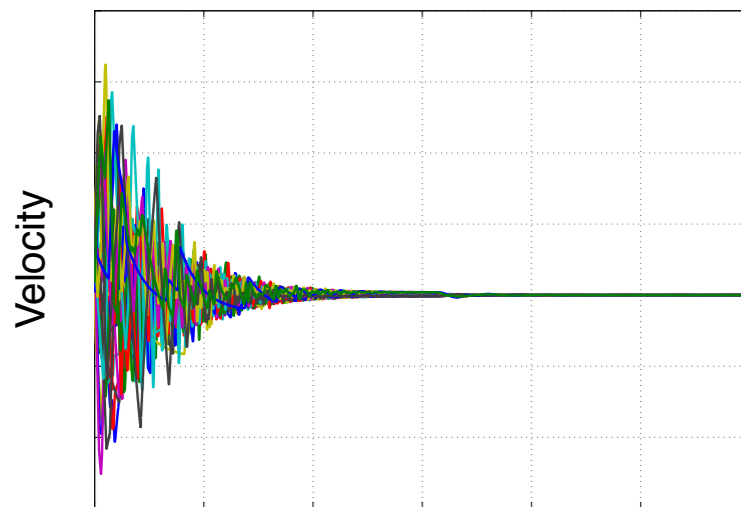
[Helbing *et al.*, 2001]

$$\dot{p}_i = v_i$$

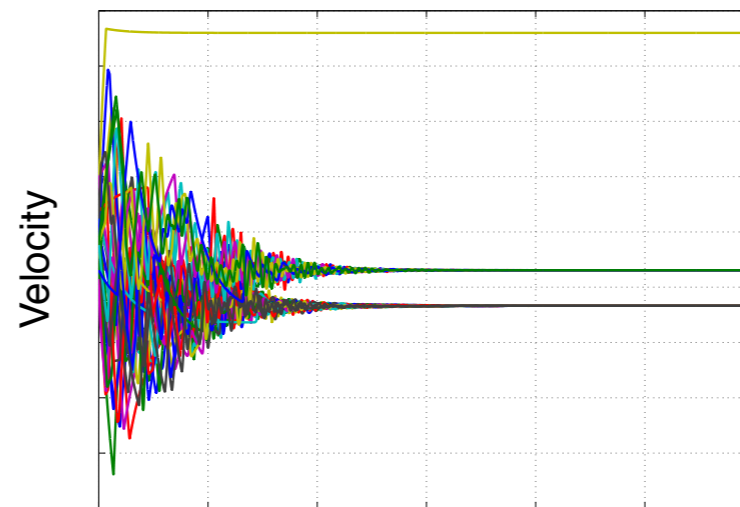
$$\dot{v}_i = \kappa_i [V_i^0 + V_i(\nabla \mathbf{p}) - v_i]$$

Velocity adjustment (control)

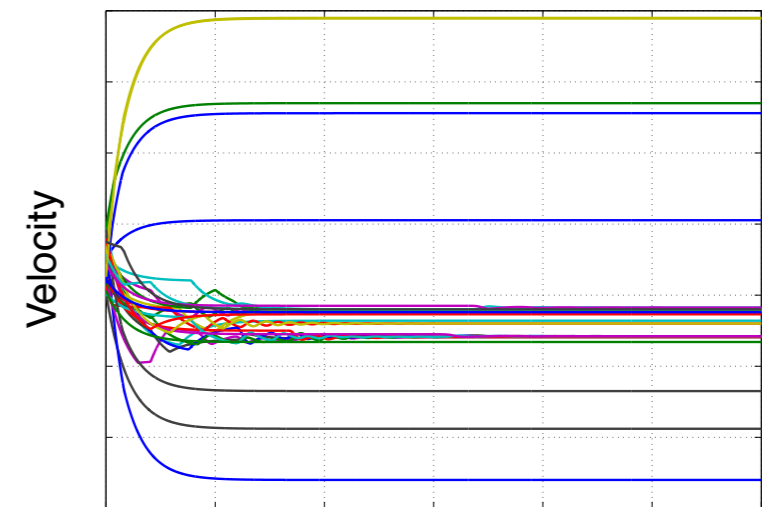
$$V_i(\nabla \mathbf{p}) = V_i^1 \sum_{j \in \mathcal{N}(i)} \tanh(p_j - p_i)$$



Time



Time



Time



An Example - Vehicle Platooning



Microscopic Traffic Model

[Helbing *et al.*, 2001]

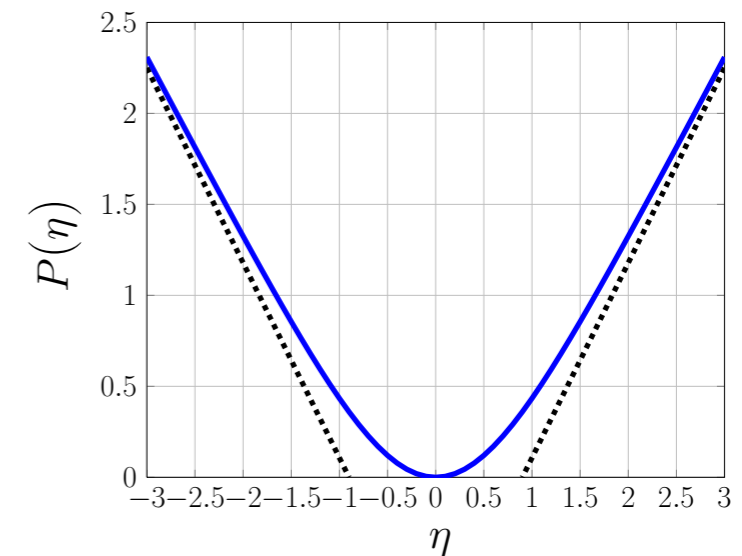
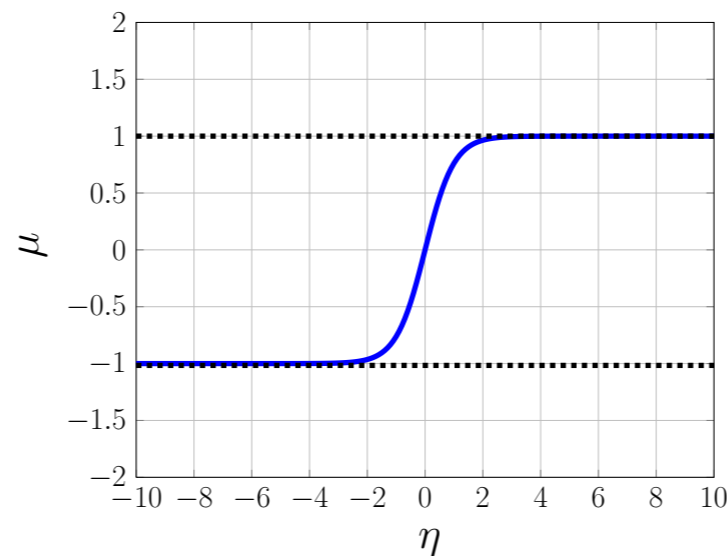
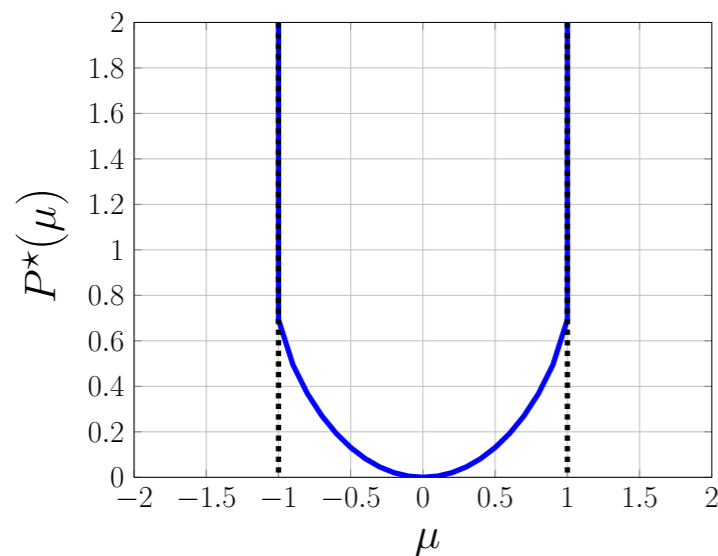
$$\dot{p}_i = v_i$$

$$\dot{v}_i = \kappa_i [V_i^0 + V_i(\nabla \mathbf{p}) - v_i]$$

Velocity adjustment (control)

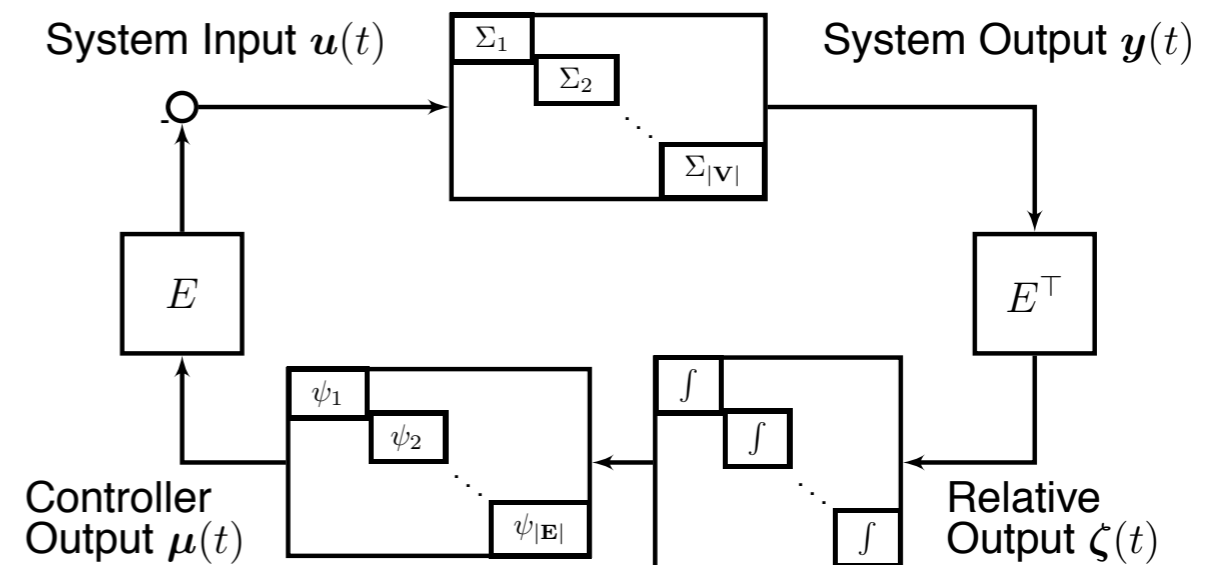
$$V_i(\nabla \mathbf{p}) = V_i^1 \sum_{j \in \mathcal{N}(i)} \tanh(p_j - p_i)$$

output coupling function is monotone, but not strongly monotone!



An Example - Vehicle Platooning

Network Optimization approach can still be used!



Optimal Flow Problem
(OFP1)

$$\min_{\mathbf{u}_i, \mu_k} \sum_{i=1}^{|\mathbf{V}|} K_i(\mathbf{u}_i)$$

$$\text{s.t. } \mathbf{u} = E\boldsymbol{\mu}$$

$$\|\boldsymbol{\mu}\|_{\infty} \leq 1$$

Optimal Potential Problem
(OPP1)

$$\min_{y_i, \zeta_k} \sum_{i=1}^{|\mathbf{V}|} K_i^*(y_i) + \sum_{k=1}^{|\mathbf{E}|} |\zeta_k|$$

$$\text{s.t. } \boldsymbol{\zeta} = E^{\top} \mathbf{y}$$



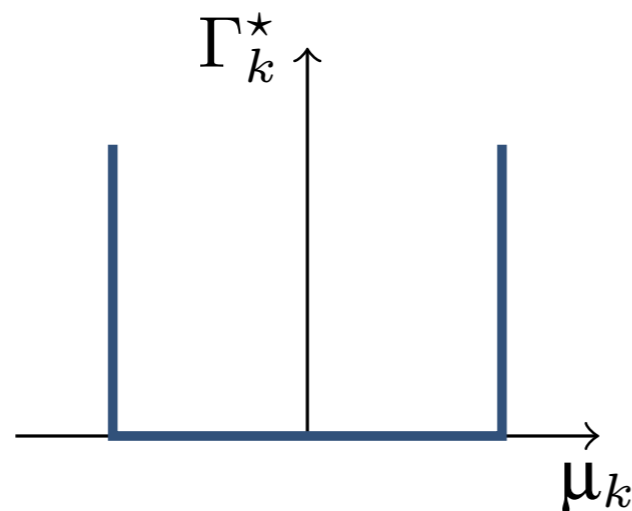
An Example - Vehicle Platooning

Optimal Flow Problem
(OFP1)

$$\min_{\mathbf{u}_i, \mu_k} \sum_{i=1}^{|\mathbf{V}|} K_i(\mathbf{u}_i)$$

$$\text{s.t. } \mathbf{u} = E\boldsymbol{\mu}$$

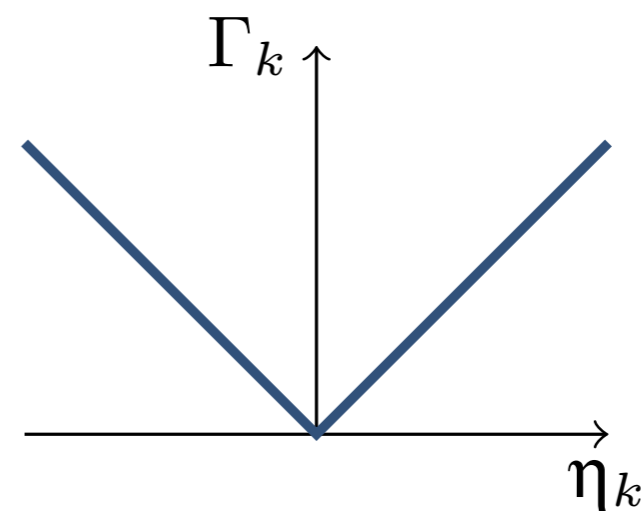
$$\|\boldsymbol{\mu}\|_{\infty} \leq 1$$



Optimal Potential Problem
(OPP1)

$$\min_{y_i, \zeta_k} \sum_{i=1}^{|\mathbf{V}|} K_i^*(y_i) + \sum_{k=1}^{|\mathbf{E}|} |\zeta_k|$$

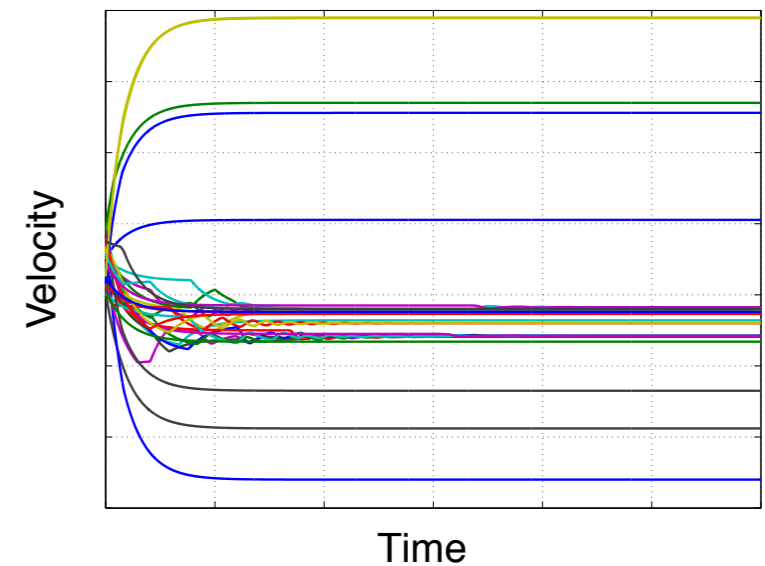
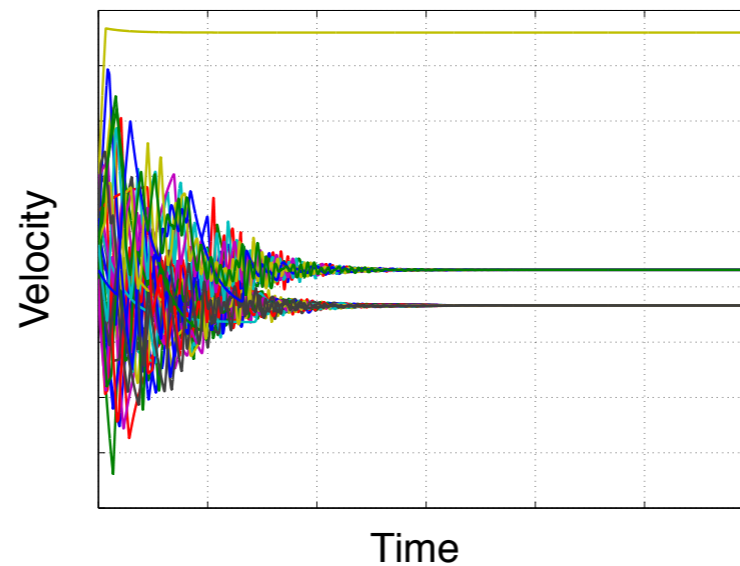
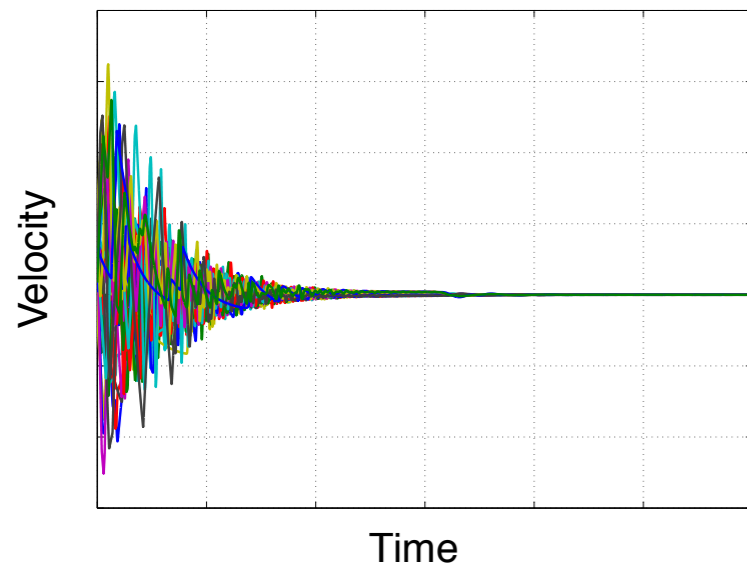
$$\text{s.t. } \boldsymbol{\zeta} = E^{\top} \mathbf{y}$$



additional objective functions corresponding
to “flow capacity” constraints



An Example - Vehicle Platooning



clustering phenomena can be explained by studying the solutions of the static network optimization problems

$$\min_{\mathbf{u}_i, \mu_k} \sum_{i=1}^{|\mathbf{V}|} K_i(\mathbf{u}_i)$$

$$\text{s.t. } \mathbf{u} = E\boldsymbol{\mu}$$

$$\|\boldsymbol{\mu}\|_{\infty} \leq 1$$

$$\min_{y_i, \zeta_k} \sum_{i=1}^{|\mathbf{V}|} K_i^*(y_i) + \sum_{k=1}^{|\mathbf{E}|} |\zeta_k|$$

$$\text{s.t. } \boldsymbol{\zeta} = E^{\top} \mathbf{y}$$

Towards a Synthesis Procedure

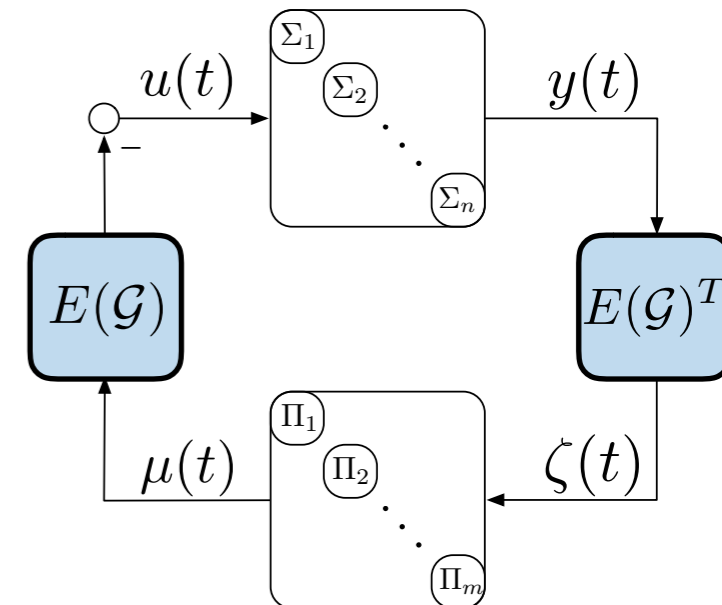
Design controllers to achieved a *desired* output agreement state.

Generalized Optimal Potential Problem
(OPP1)

$$\min_{\mathbf{y}, \boldsymbol{\zeta}} \sum_{i=1}^{|\mathbf{V}|} K_i^*(y_i) + \sum_{k=1}^{|\mathbf{E}|} \Gamma_k(\zeta_k)$$

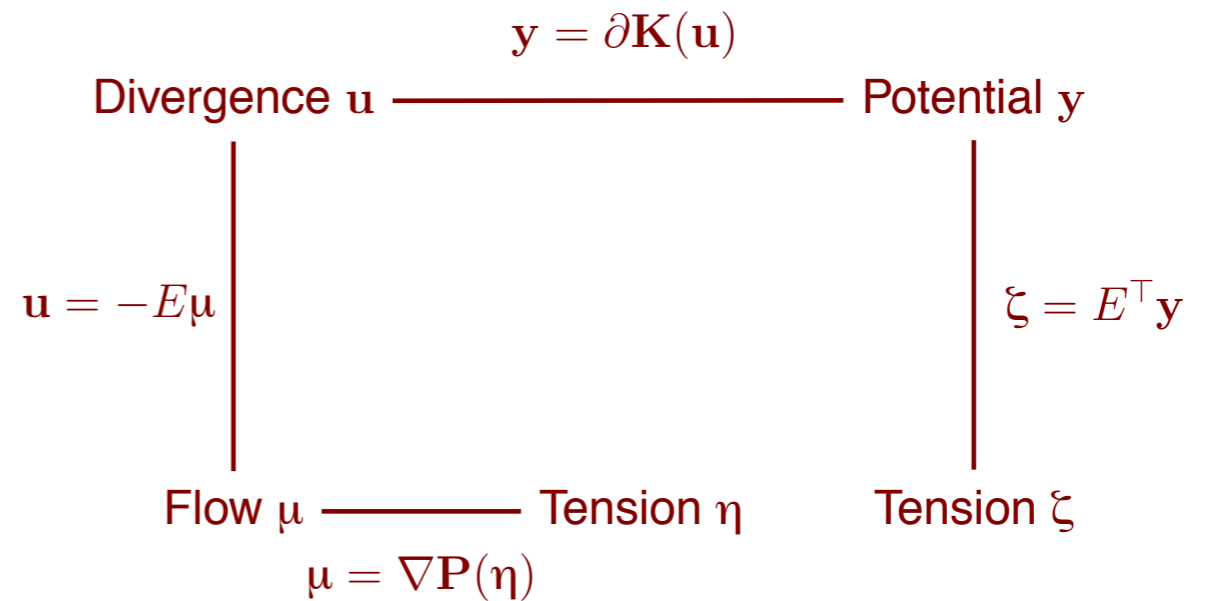
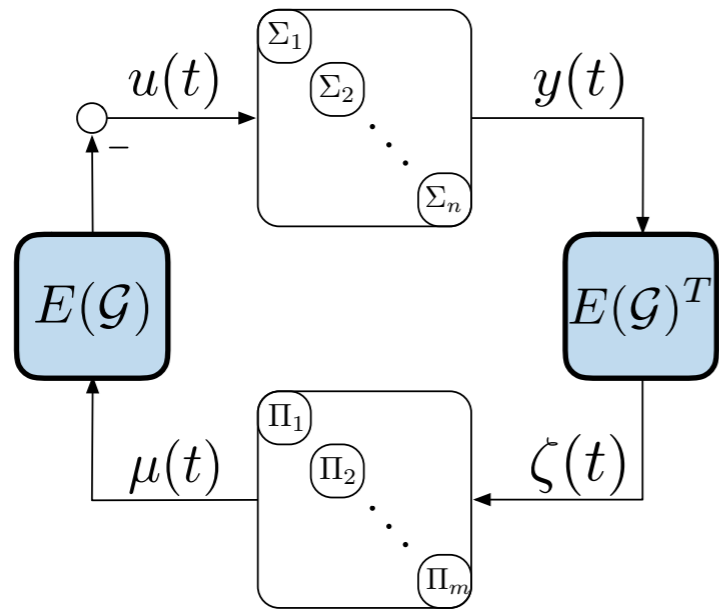
s.t. $\boldsymbol{\zeta} = E^T \mathbf{y}$.

1. Find a convex function Γ such that the desired output agreement state, y^* satisfies $\zeta^* = E^T y^*$ and minimizes the GOPP.
2. Find Maximal EIP systems whose steady-state input-output maps are the subdifferentials of the functions Γ_i .



Summary

Passivity based cooperative control

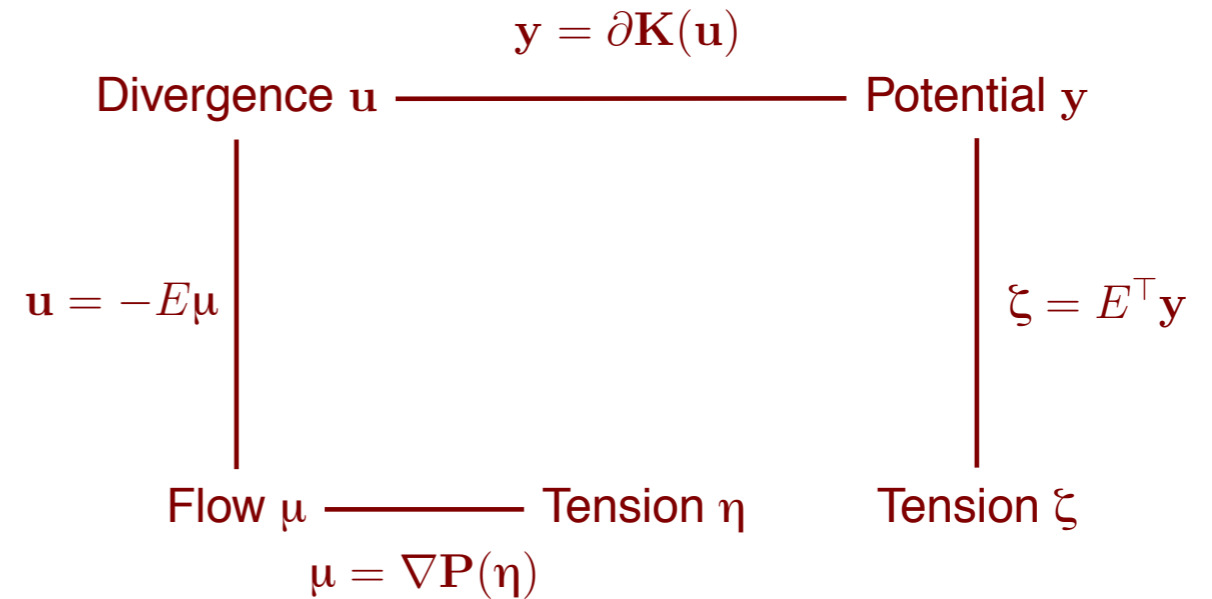
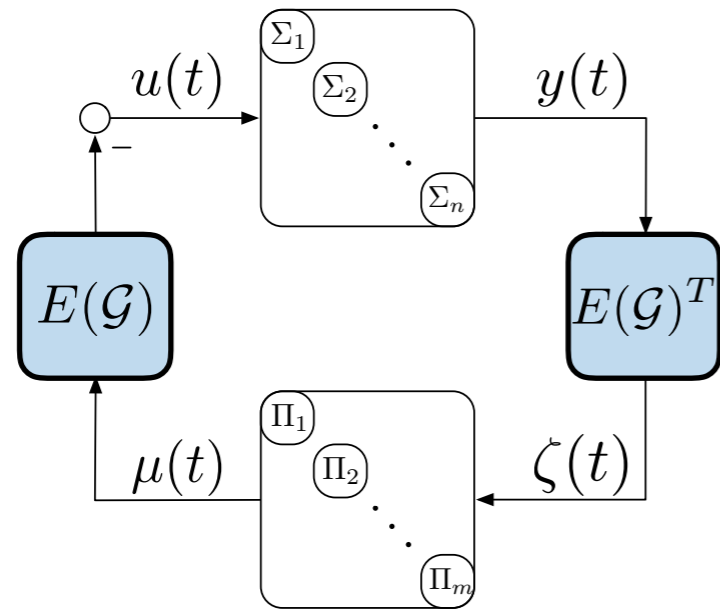


- maximal EIP systems
- connection to dual network optimization problems
- maximal EIP implies agreement solution is *inverse optimal*
- **duality relation exists for cooperative control problems!**



Outlook

Passivity based cooperative control



- further extensions to MIMO systems
- controller synthesis
- “Duality” as a systems property

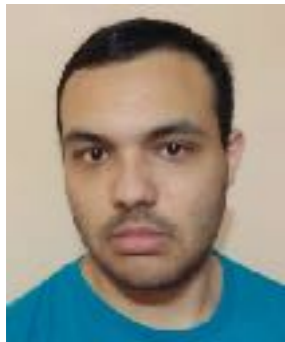
Acknowledgements



Prof. Dr.-Ing. Frank Allgöwer
Institute for Systems Theory
and Automatic Control



Dr. Mathias Bürger
Cognitive Systems Group
at Robert Bosch GmbH



Miel Sharf
Technion

- [1] M. Bürger, D. Zelazo, and F. Allgöwer, "Duality and network theory in passivity-based cooperative control," *Automatica*, 50:2051-2061, 2014.
- [2] M. Sharf and D. Zelazo, "Cyclically-Monotone Relations and their use in Passivity-Based Cooperative Control," *in preparation*, 2017.

Thank-you!
Questions?

