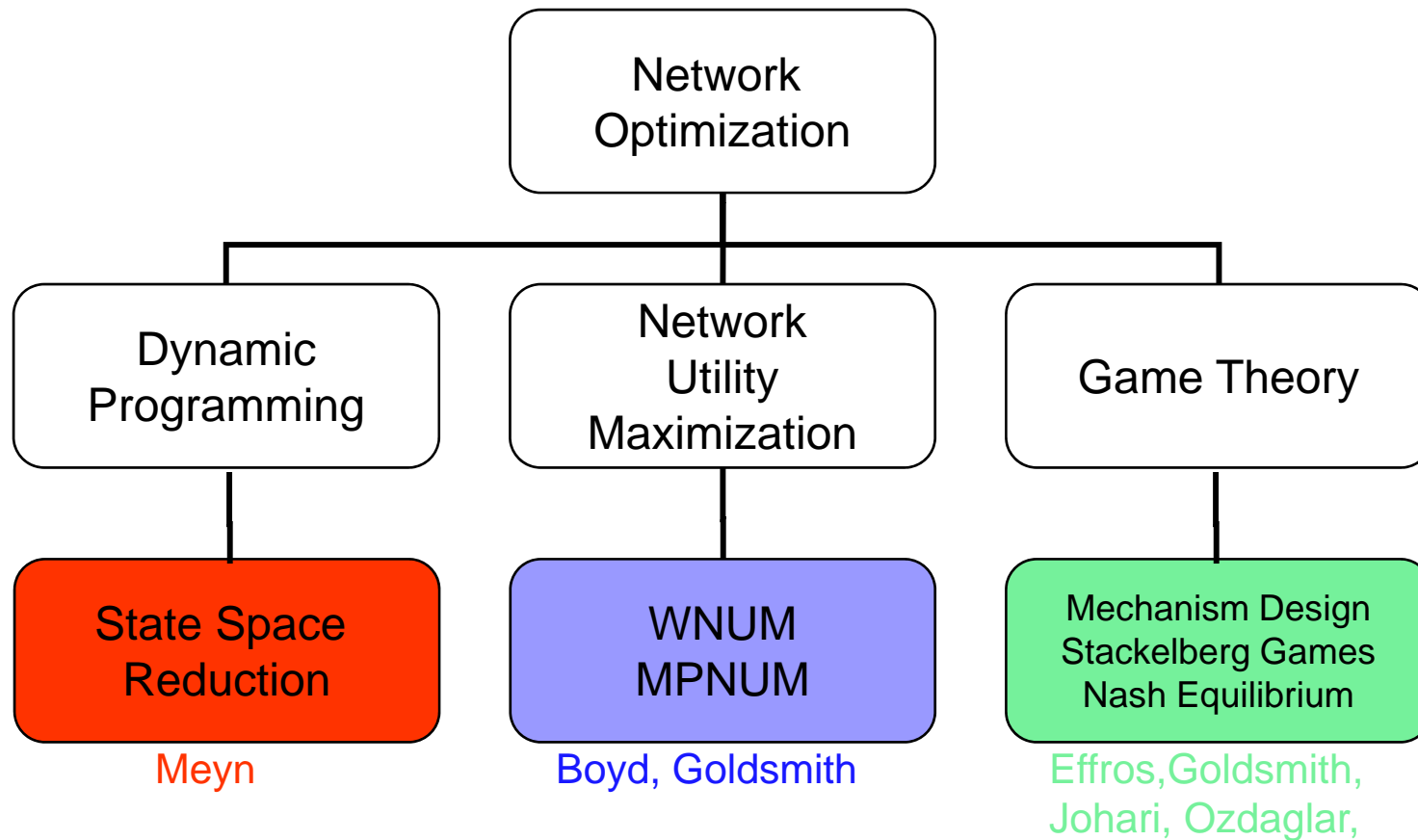




Optimizing Wireless Network Performance in Random Environments

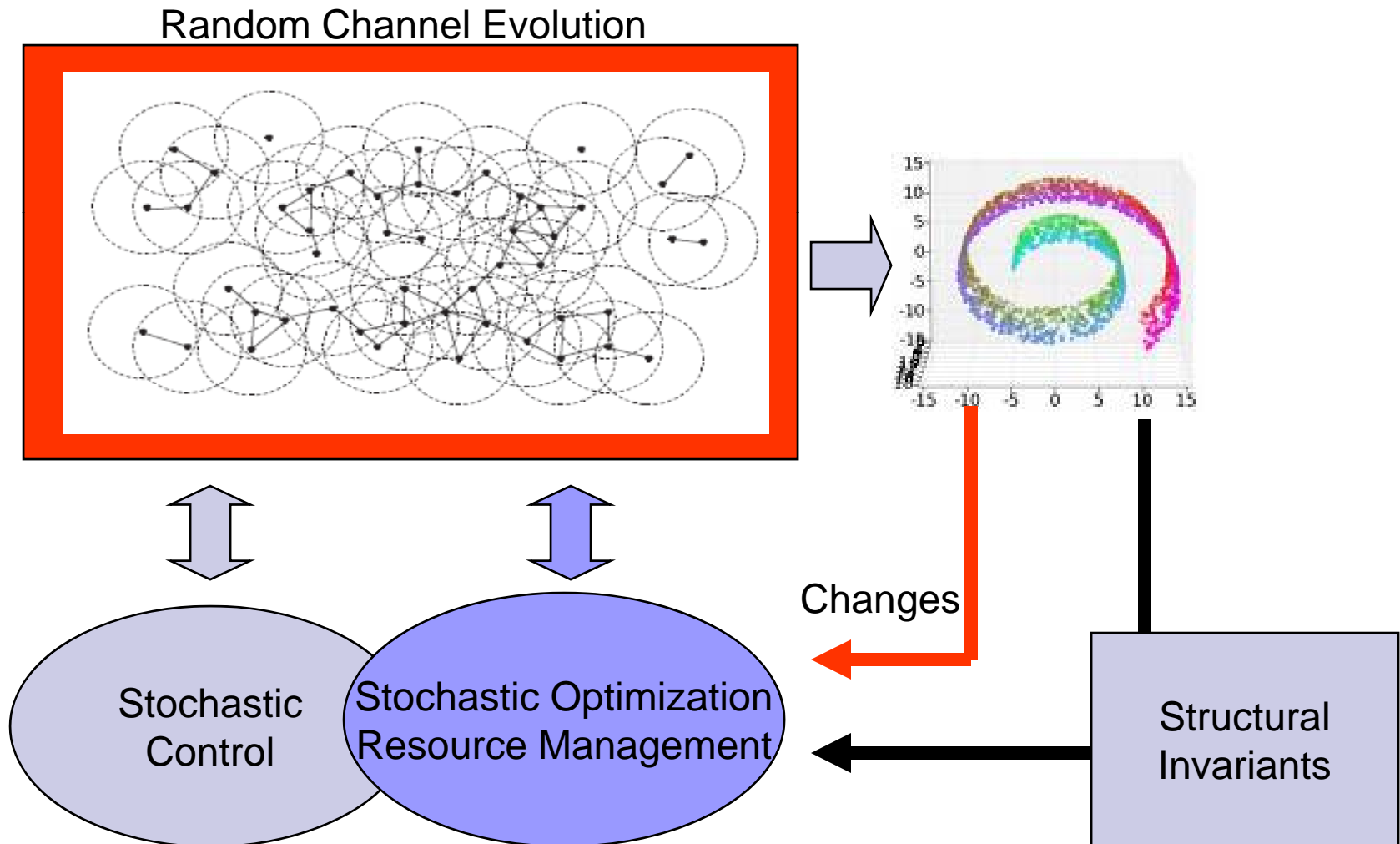
Stephen Boyd
Andrea Goldsmith
Daniel O'Neill

Approaches to Network Optimization*



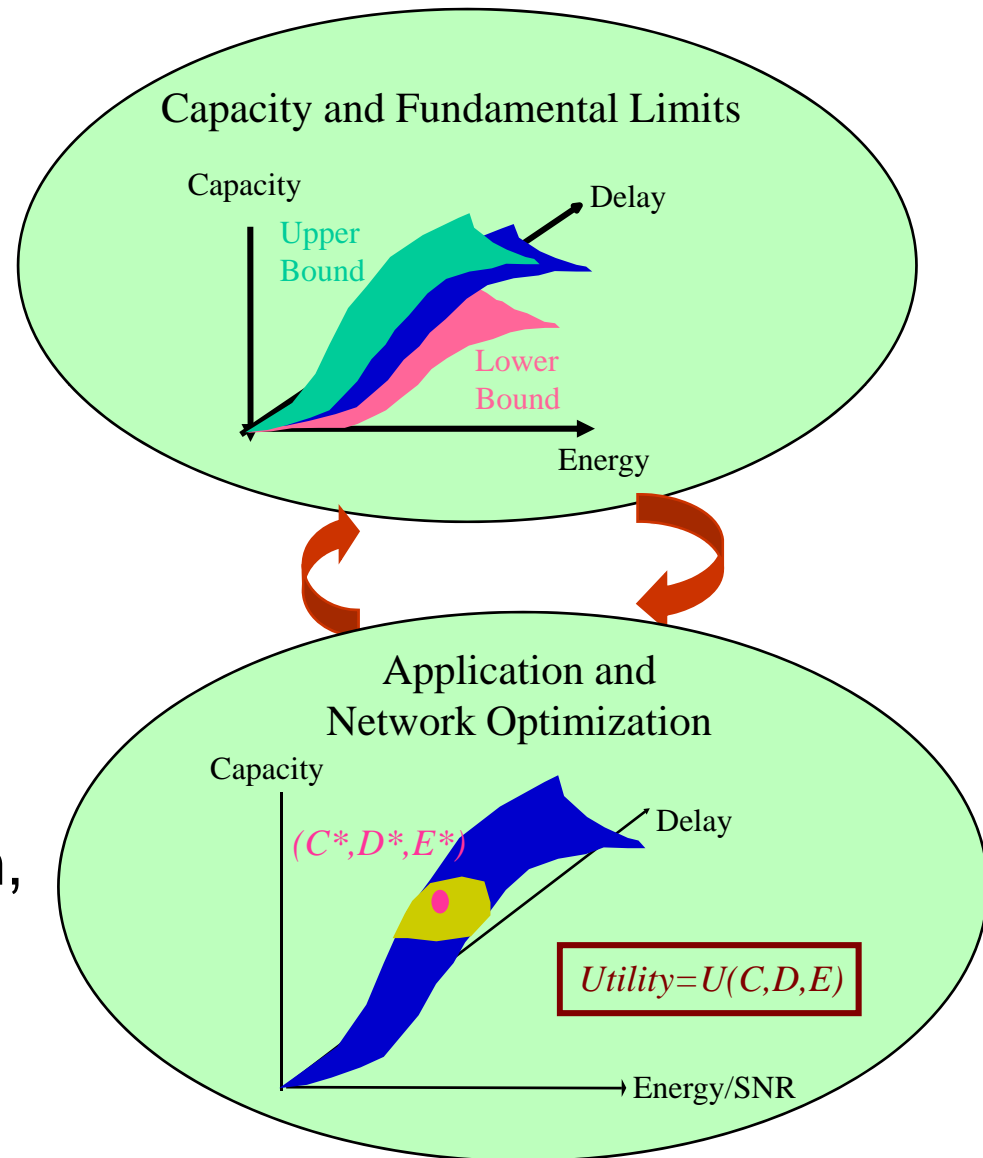
*Most prior work is for wired/static networks

Optimization requires models and tools



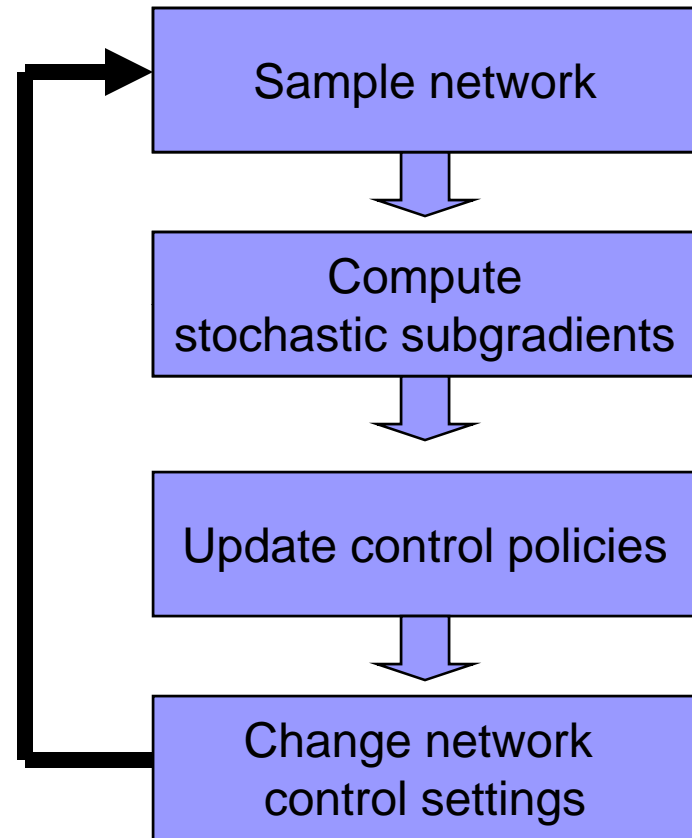
Models come from Thrusts 1 and 2

- Time-varying capacity regions define underlying link rates
- Currently incorporating generalized relaying at PHY into model
- When models unknown, need online learning



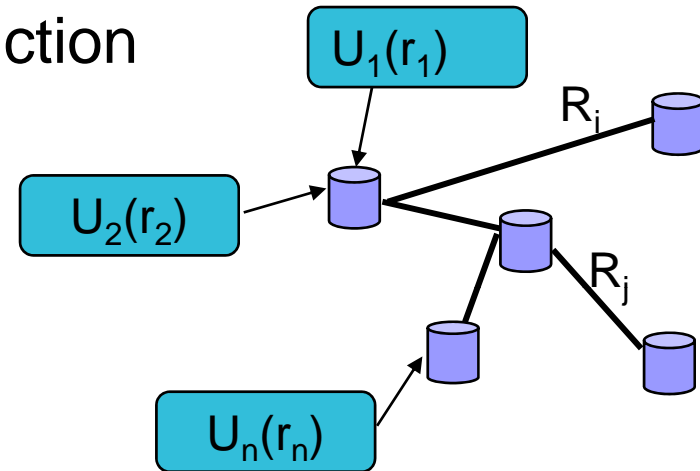
On-Line Learning

- Samples network
- Iteratively finds best control policies
- Application of stochastic approximation



Network Utility Maximization

- Maximizes a network utility function
- Assumes
 - Steady state
 - Reliable links
 - Fixed link capacities
- Dynamics are only in the queues



$$\begin{aligned} \max \quad & \sum U_k(\overset{\text{flow } k}{r_k}) \\ \text{s.t.} \quad & \underset{\text{routing}}{A} r \leq \underset{\substack{\text{Fixed link} \\ \text{capacity}}}{R} \end{aligned}$$

Wireless NUM

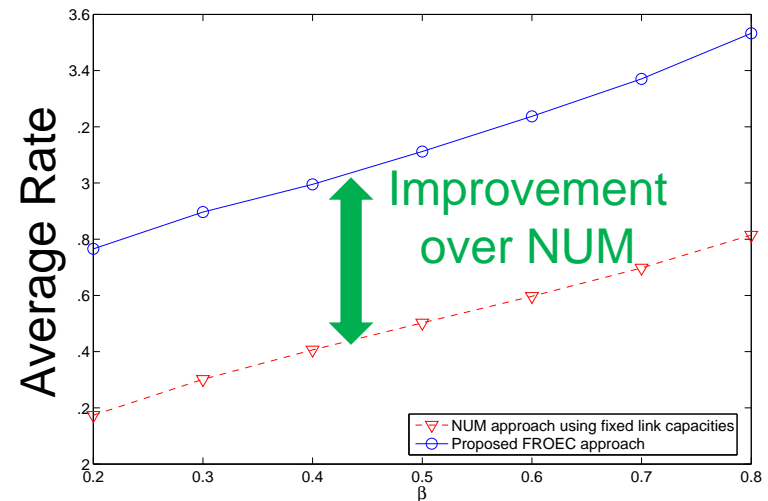
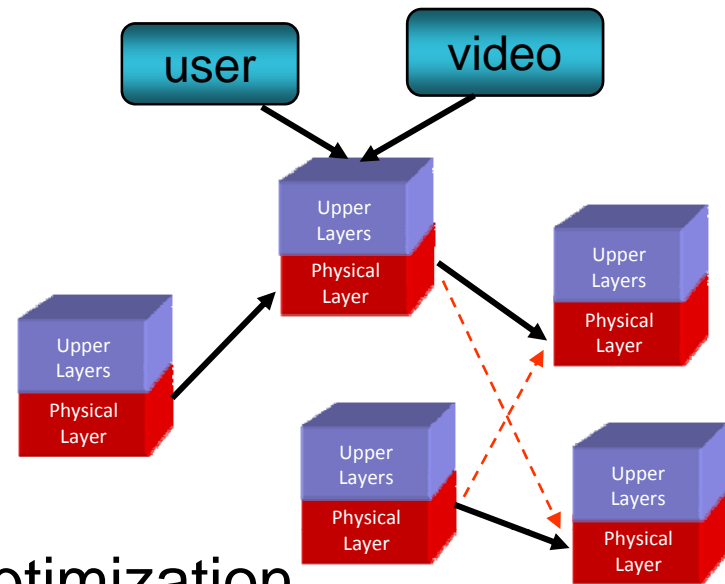
- Extends NUM to wireless networks
 - Random lossy links
 - Error recovery mechanisms
 - Network dynamics

- Network control as stochastic optimization

$$\begin{aligned} \max \quad & E[\sum U(r_m(G))] \\ \text{st} \quad & E[r(G)] \leq E[R(S(G), G)] \\ & E[S(G)] \leq \bar{S} \end{aligned}$$

- Next steps

- Adaptive PHY layer and reliability
- Existence convergence properties
- Channel estimation errors





Beyond WNUM

■ WNUM Limitations

- Adapts to channel and network dynamics
- Cross-layer optimization of PHY and higher layers
- *But* limited to elastic traffic flows

■ MPNUM extends WNUM

- Traffic can have defined start and stop times
- Traffic QoS metrics can be met
- General capacity regions can be incorporated
- Multiple time periods explicitly captured

Multi-Period Stochastic Control of Networks

Stephen Boyd and Ekine Akuiyibo

ITMANET PI meeting 03/5-6/09

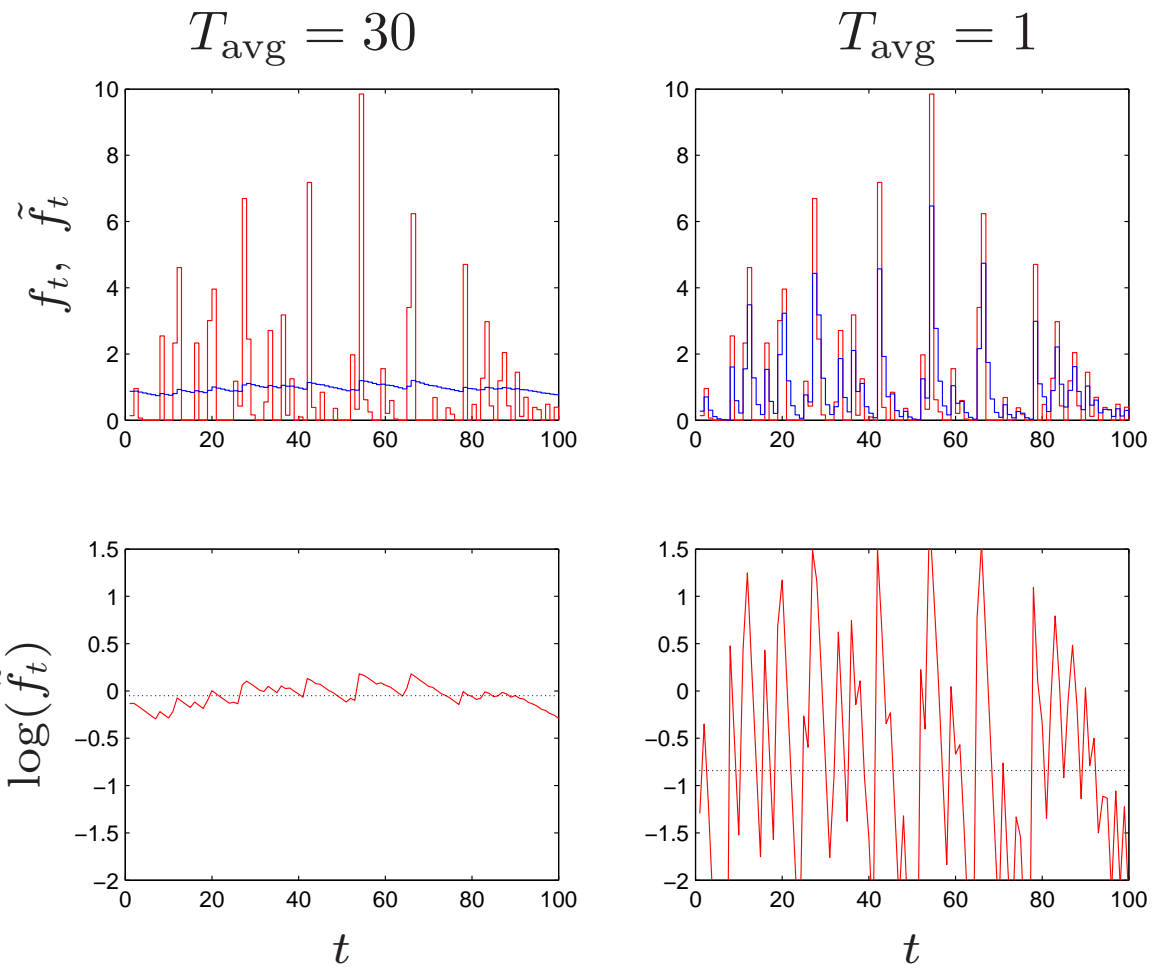
The problem and issues

- goal: multi-period resource (*e.g.*, flow rate, power) allocation
- resources (*e.g.*, link capacities, channel states) vary randomly
- maximize utility (or minimize cost) that reflects different
 - weights (priorities)
 - desired/required target levels
 - **averaging time scales**for different flows
- unifies what we called before WNUM, DNUM, SNUM

Dynamic utility and averaging time scale

- f_t is flow in period t , $t = 0, 1, \dots$
- $U : \mathbf{R} \rightarrow \mathbf{R}$ gives utility derived for a flow value
- $\tilde{f}_t = (1 - \theta) \sum_{\tau=0}^t \theta^\tau f_{t-\tau}$ is (first order) **smoothed** or **averaged** flow
- $T_{\text{avg}} = 1 / \log(1/\theta)$ gives smoothing time scale
- average smoothed utility is $\bar{U} = \lim_{t \rightarrow \infty} (1/t) \mathbf{E} \sum_{\tau=0}^t U(\tilde{f}_\tau)$
- when U is not linear, \bar{U} depends on smoothing time scale T_{avg}
- our claim: flow utility should be judged dynamically, *i.e.*, by a **utility function** and an **averaging time scale**

Example



Utility state

- represent smoothing via linear dynamical system
- $f_t \in \mathbf{R}^n$ is vector of flows
- $x_{t+1} = \Theta x_t + (I - \Theta)f_t$, $\Theta = \mathbf{diag}(\theta)$
- $(x_t)_i = \tilde{f}_i(t)$ is smoothed flow or **utility state**
- average smoothed utility is

$$\bar{U} = \lim_{t \rightarrow \infty} (1/t) \mathbf{E} \sum_{\tau=0}^t \sum_{i=1}^n U((x_{\tau})_i)$$

Stochastic flow control

- must have $f_t \in \mathcal{R}_t$ (rate region)
- in general, \mathcal{R}_t is random process on sets; we'll assume \mathcal{R}_t are IID
- stochastic flow control:
choose f_t as function (policy) of \mathcal{R}_t, x_t , to maximize \bar{U}
- can solve in principle via DP
- can solve exactly in only a few special cases
- lots of approximate solution methods

Linear quadratic formulation

- a special case for which we can get the exact solution
- rate region is defined by (random) capacity c_t : $\mathcal{R}_t = \{z \mid \mathbf{1}^T z = c_t\}$
- utilities are concave quadratic: $U(z) = -(x - x^{\text{tar}})^T Q (x - x^{\text{tar}})$
(*e.g.*, negative mean square deviation from target values)
- leads to (nonstandard) linear quadratic stochastic control problem
 - has random equality constraints
 - value function is quadratic; can be found from a Riccati-like recursion
 - optimal control law is messy, but affine in x_t, c_t

Optimal policy

- optimal policy is $f_t = Kx_t + wc_t + s$
- K, w, s found by complicated formulas and iterations
- $\mathbf{1}^T K = 0, \mathbf{1}^T w = 1, \mathbf{1}^T s = 0$, so we have $\mathbf{1}^T f_t = c_t$ (i.e., $f_t \in \mathcal{R}_t$)
- interpretations:
 - w gives the capacity allocation
 - s is an offset
 - K is the utility state to flow gain matrix

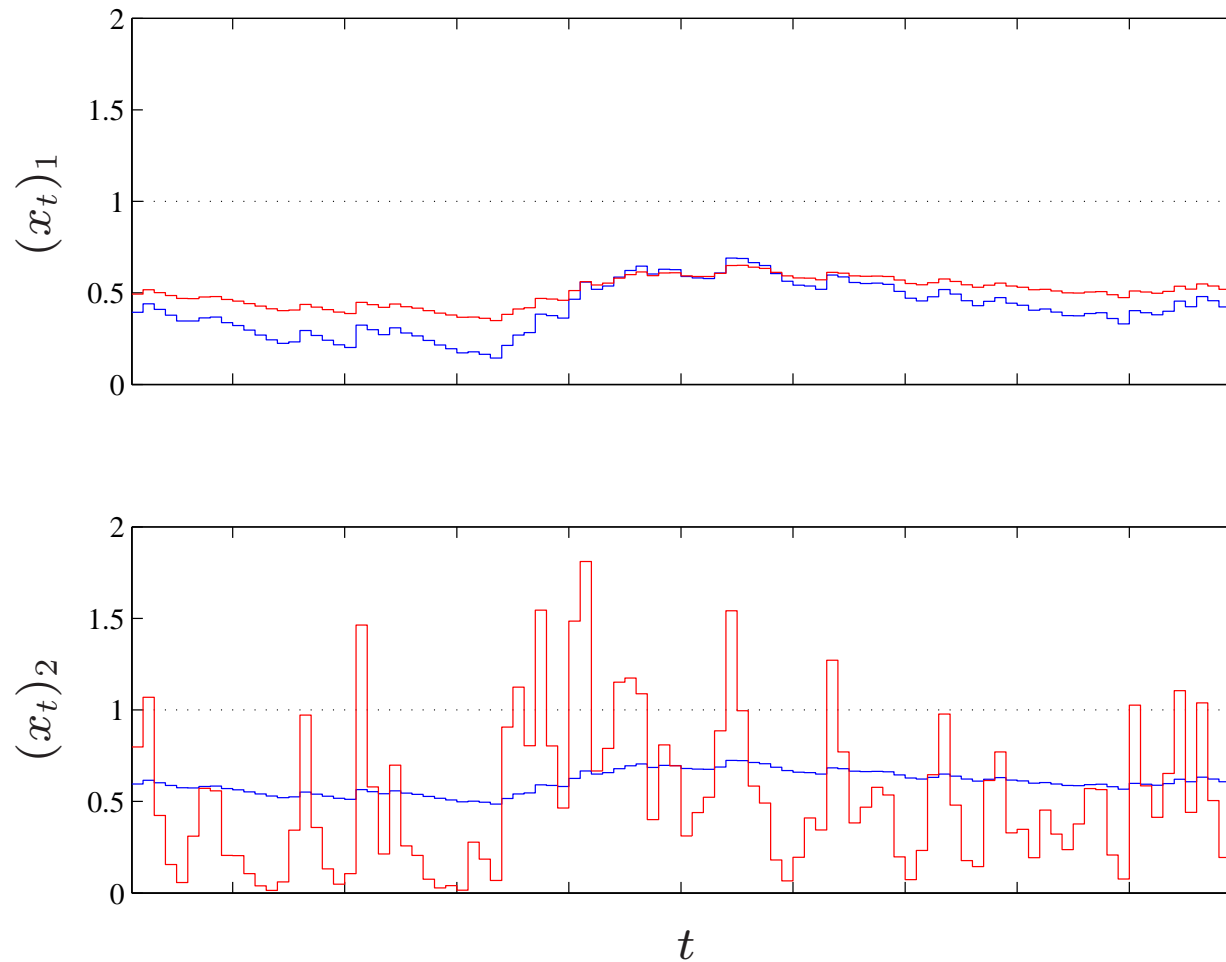
(Simplest possible) example

- 2 flows share one link
- $U(a) = -(a - 1)^2$ (i.e., target flow values are one)
- smoothing times $T_{\text{avg}} = 1, T_{\text{avg}} = 30$
- link capacity c_t is exponential with mean 1.5
- optimal policy:

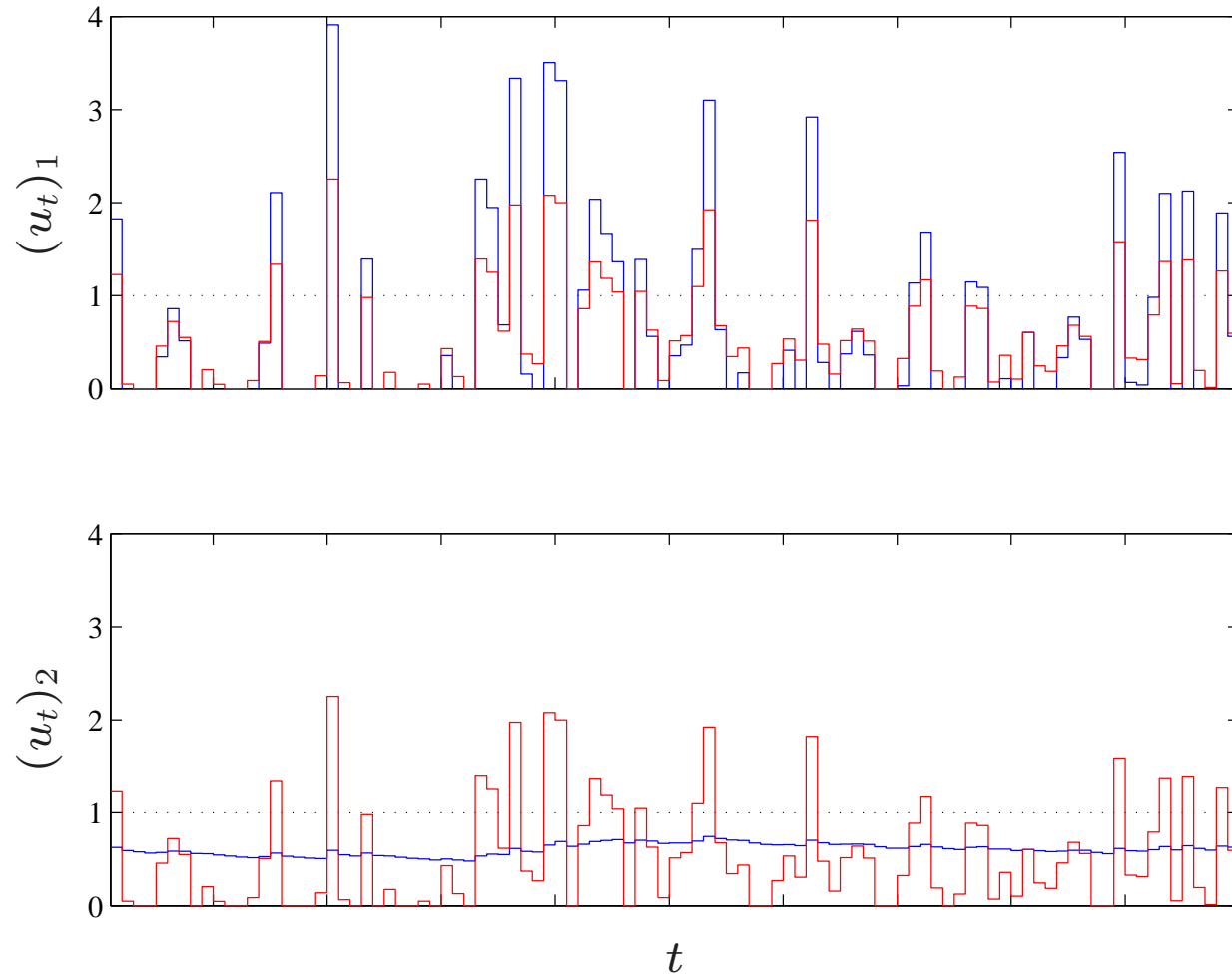
$$f_t = \begin{bmatrix} -0.652 & 0.570 \\ 0.652 & -0.570 \end{bmatrix} x_t + \begin{bmatrix} 0.978 \\ 0.022 \end{bmatrix} c_t + \begin{bmatrix} -0.655 \\ 0.655 \end{bmatrix}$$

- we'll compare with simple sharing: $f_t = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} c_t$

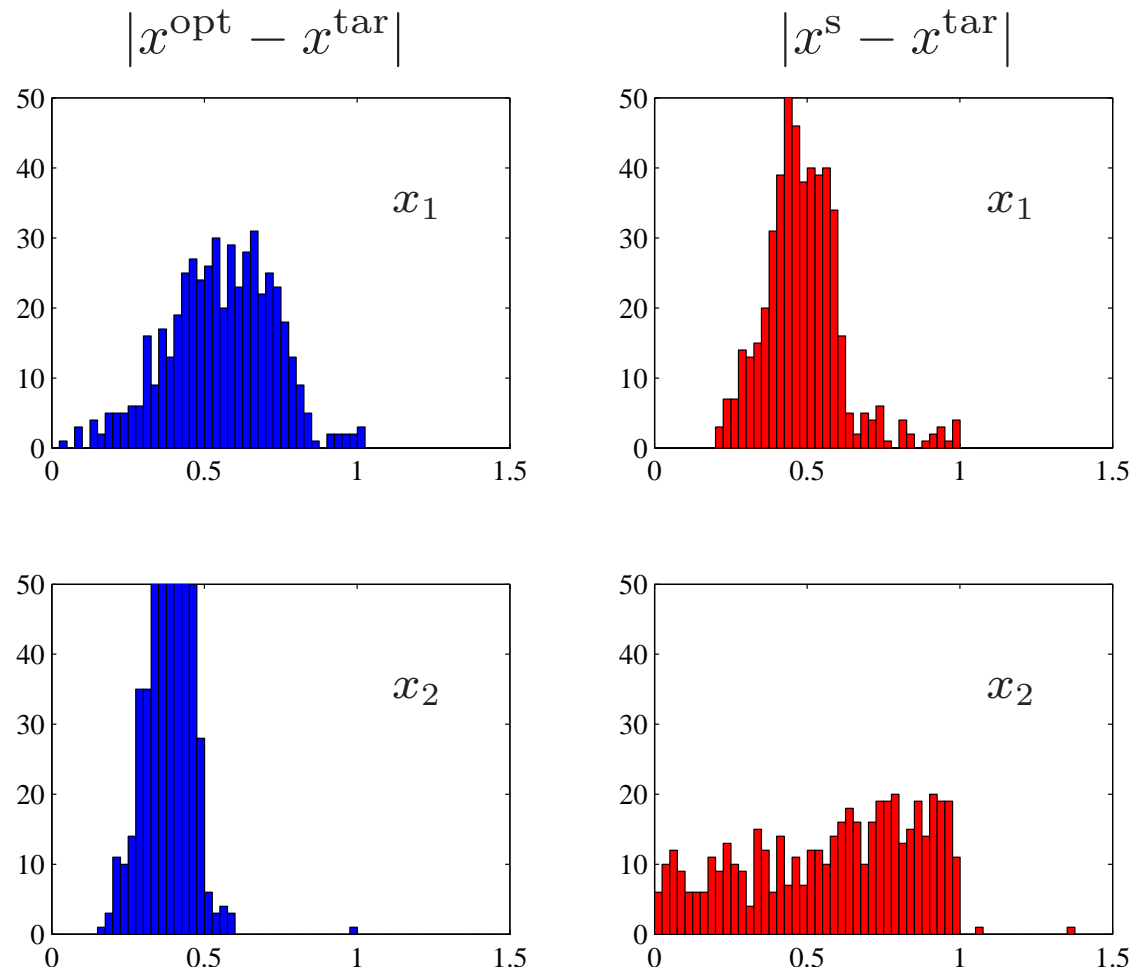
Sample trajectories—smoothed flow



Sample trajectories—flow



Error histograms



What's next

- handling inequality constraints (*e.g.*, $f_t \geq 0$, $Rf_t \leq c_t$) via control Lyapunov methods
- extension to multi-flow, multi-hop, store-and-forward (easy)
- approximating general concave utilities as quadratic
- decentralization