

# Network Science and Its Application in Wireless Networking

Dapeng Oliver Wu

Electrical & Computer Engineering  
University of Florida

# Outline

- Definition of network science
- Major problems in network science
- Application domains
  - Power grid
  - Cognitive/logical/semantic networks
  - Economic networks, e.g., stock markets
  - Biological networks, e.g., brain networks
  - Social networks
  - Information networks
  - Hybrid: information network & social network
- Major approaches in network science
- Joint congestion control and scheduling in wireless networks

# What is Network Science? (1)

- Network science is a new and emerging scientific discipline concerned with the interconnections among elements within a system/network.
  - physical or engineered networks (e.g., power grid, and transportation network)
  - information networks
  - biological networks (e.g., brain network, gene regulatory network, neural network)
  - Cognitive/logical/semantic networks (e.g., concept/topic networks)
  - economic networks (e.g., stock market)
  - social networks

# What is Network Science? (2)

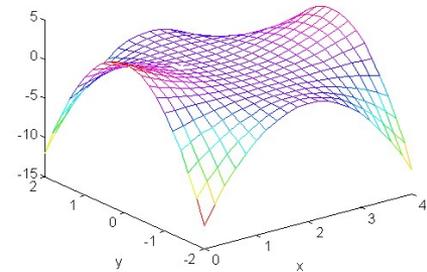
- This field of science seeks to discover common principles, algorithms and tools that govern
  - network structures/topologies
  - network functionalities
  - network behaviors.

# Three Major Problems in Network Science

- Network sampling problem:
  - network Nyquist sampling theorem?
- Graph learning problem:
  - identify the network structure/topology.
- Identification of network dynamics/behaviors:
  - identify the ODE/PDE/SDE model of each node in the network
  - estimate the parameters of the model

# Network Sampling Problem

**Given a 2D random field  $f(x, y)$ , where  $(x, y)$  can be continuous or discrete, find the optimal locations of  $N$  sensors with measurements  $f_i$  ( $i = 1, \dots, N$ ) such that **MSE**  $\iint (f(x, y) - \hat{f}(x, y))^2 dx dy$  is minimized, where  $\hat{f}(x, y)$  is reconstructed from  $f_i$  ( $i = 1, \dots, N$ ).**

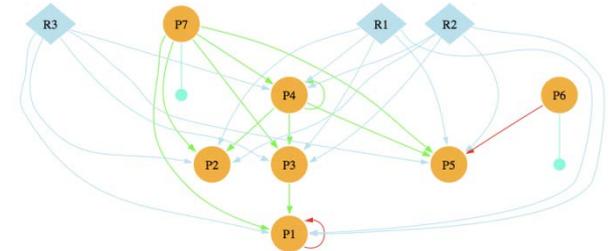


- Does Network Nyquist sampling rate exist?
- Solving this problem has broad implications, e.g.,
  - How to deploy sensors so that the probability of detecting vehicles/tanks, gunshots, fire in the area is maximized
  - How to deploy traffic monitors so that the probability of detecting the locations of anomalies in communication networks is maximized
  - How to deploy sensors so that the probability of detecting terrorist activities is maximized

# Graph Learning Problem

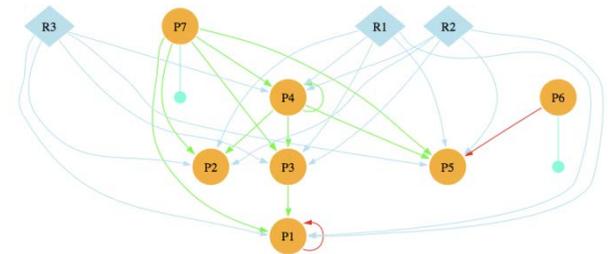
**For a network of  $K$  nodes, assume the state of each node can be measured. Given  $N$  samples of the state of each node  $x_{i,j}$ , ( $i = 1, \dots, K$ ;  $j = 1, \dots, N$ ) where  $i$  denotes node index, and  $j$  denotes sample index, identify the network topology, i.e., whether there is a link between Node  $i$  and Node  $k$ , where  $i \neq k$ , and  $i, k = 1, \dots, K$ .**

- Implications:
  - Identify the topology of
    - gene regulatory networks, given micro-array data
    - social networks, given telephone records of a community, or messages in Internet chat-rooms.
    - semantic networks of words/phrases, given text documents
    - brain networks/connectome, given fMRI or Brainbow images



# Identification of Network Dynamics/Behaviors

- Assume the state of each node in a network is time-varying
  - Model each node by a dynamic system
  - Characterize each node by ODE/PDE/SDE
  - Problem: given samples of the state of each node, identify/estimate the parameters of ODE/PDE/SDE
- Implications:
  - A gene regulatory network may change over time; need to model it as a dynamic network
  - Same for a social network



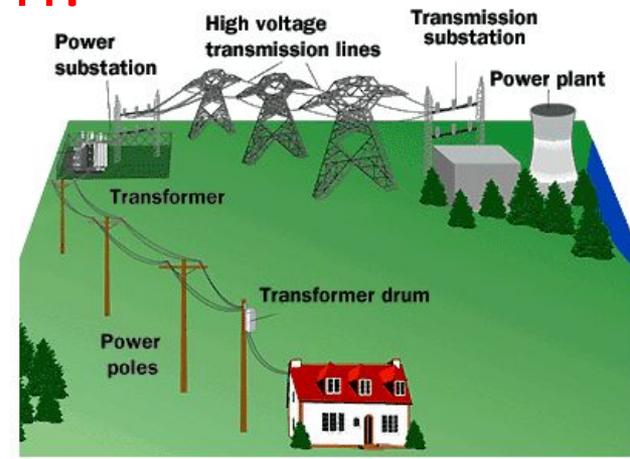
# Outline

- Definition of network science
- Major problems in network science
- **Application domains**
  - Power grid
  - Cognitive/logical/semantic networks
  - Economic networks, e.g., stock markets
  - Biological networks, e.g., brain networks
  - Social networks
  - Information networks
  - Hybrid: commodity/energy/money/human flows
- Major approaches in network science
- Joint congestion control and scheduling in wireless networks

# Power Grid

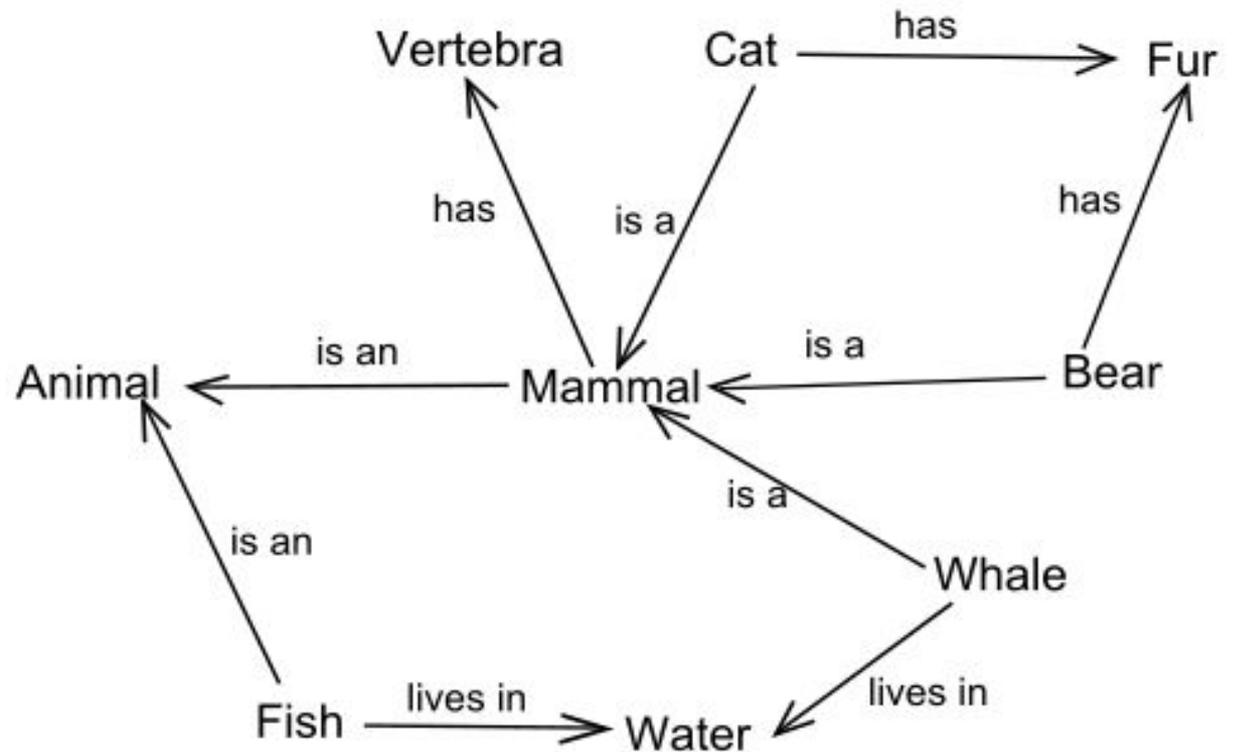
- How does network topology affect the robustness? Vulnerability analysis
- How to model the dynamics of large-scale power grid?
- Is it possible to predict large-scale blackouts?
- How to prevent large-scale blackouts?

➡ **very challenging problem!**



# Semantic Networks

- How to extract a semantic network, given samples such as terms and text documents



# Economic Networks

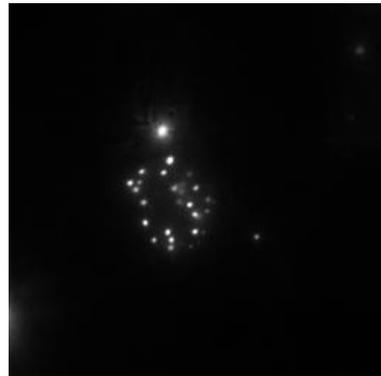
- How to detect bubbles in stock market, given stock prices and news
  - ➡ you can make a fortune out of it, if you can predict a bubble accurately
- How to detect economic bubbles, given economic data



SLB	4.70	0.03	-0.70%	0.0	1
MAL	4.36	-0.33	-0.03%	0.03	1
NE	2.42	-0.01	-1.5%	0.0	1
NV	5.64	0.07	-0.02%	-0.05	1
QTVV	2.95	0.32	-1.58%	-0.01	1
HYOS	9.13	-0.01	1.32%	0.0	1
PLUG	11.61	-0.04	-0.18%	-0.35	1
ESLR	21.14	-0.05	-1.34%	0.17	1
LMT	26.37	-0.11	-0.54%	-0.67	1
CD	62.20	-0.04	-0.94%	0.11	1
IOC	21.77	-0.01	-0.19%	-0.01	1
TN	21.77	0.53	-0.04%	0.0	1
	26.6	0.13	0.86%	0.07	6
	19.59	-0.35	0.6%	0.0	3
	49.06	0.09	-1.3%	0.09	3
	39.16	-0.16	0.46%	-0.11	26
			-0.33%	0.0	4
				0.06	5

# Biological Networks

- Problem: identify those nuclear bodies whose behaviors are correlated, given fluorescence microscopy images
- Implications
  - Physical bio-marker for early cancer detection
  - Help understand the mechanisms of cell movement (motility)



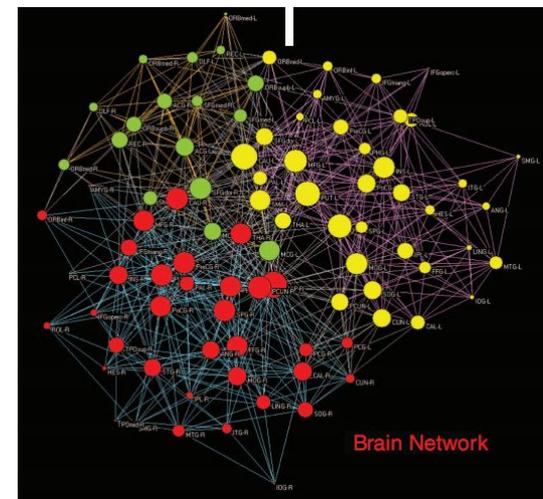
Cancer cell



Normal cell

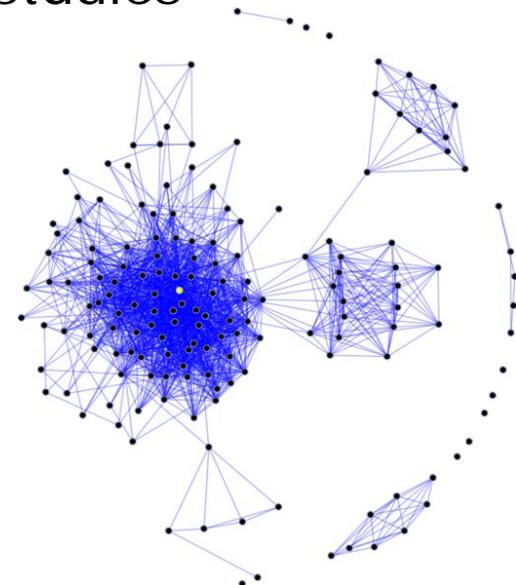
# Brain Networks

- How to identify the structure of a brain network, i.e., brain connectome
- Parcellation/clustering, registration, change detection
- Implications
  - A connectome is fundamentally important for understanding brain growth, aging, and abnormality
  - Abnormal brain connections may indicate schizophrenia, multiple sclerosis, autism, or Alzheimer's disease



# Social Networks

- How patterns of human contact affect certain phenomena, e.g., the spread of diseases, cultural changes, happiness?
- Implications
  - anthropology, epidemiology, biology, communication studies, economics, geography, information science, organizational studies, social psychology, sociology, sociolinguistics, political science, cultural studies



# Information Networks

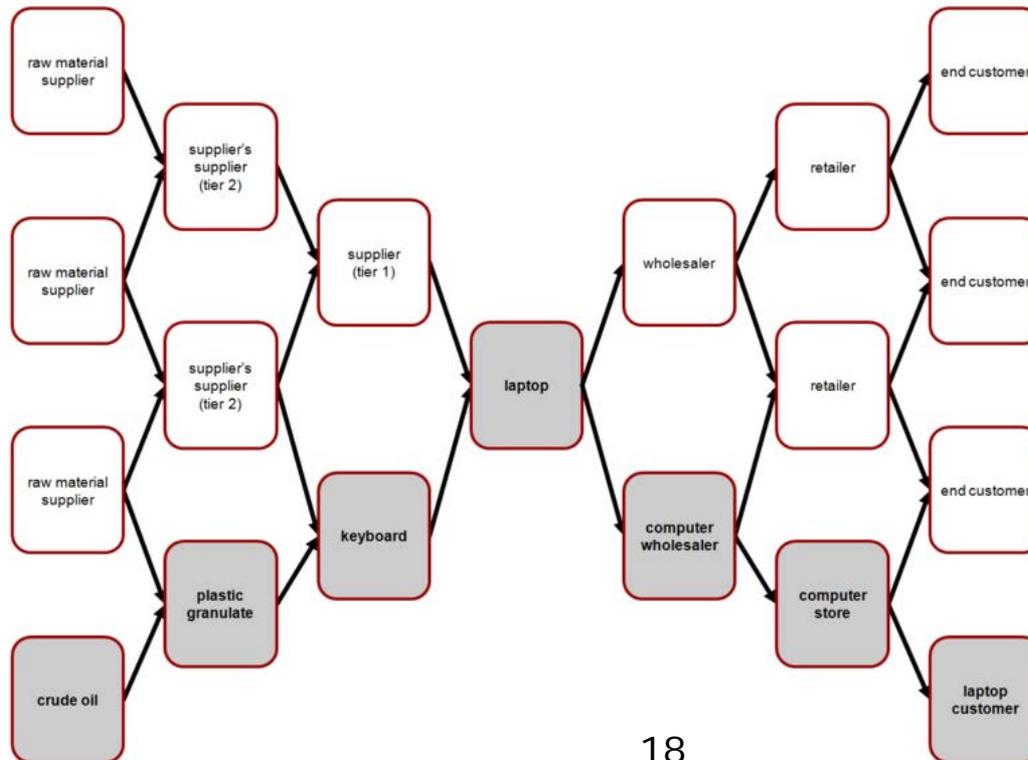
- What is the interplay between communication networks and the social networks involved
  - Online communities, e.g., Twitter, Facebook, LinkedIn
  - Wired/wireless networks, iPhone, laptop, desktop
  - Location of users: office, café, subway, bus
- Implications
  - The insights gained may help design future communication networks with desired robustness, efficiency, and security

# New Theory for Traffic Engineering

- Erlang-B and Erlang-C formulae are no longer accurate for scale-free telecom/computer networks, due to:
  - the call frequency of the phone numbers called by a caller follows power law
  - the holding time follows a heavy-tail distribution instead of an exponential distribution, which was assumed in Erlang-B and Erlang-C formulas.
  - the topology of the telecom/computer network is scale free
- A new theory for traffic engineering is needed.

# Hybrid Networks

- E.g.: Networks in economy, supply chain management, ecology
- commodity/energy/money/human flows



# Major Approaches in Network Science

- Boltzmann principle
- Gibbs principle (decomposition)
- Message-passing method
- Approximation algorithms for NP hard problems
- Compressive sensing approach for NP hard problems

# Boltzmann Principle

- Study asymptotics of a large scale problem:
  - It may be hard to obtain a solution for a small-scale problem. But a large scale problem may admit a simple solution.
  - Convert a combinatorial problem into a much simpler problem
  - E.g., Asymptotic Equipartition Property (AEP), typical set, channel capacity, large deviation theory

# Gibbs Principle

- Gibbs principle (decomposition):
  - Decompose a high-dimensional problem into multiple low-dimensional sub-problems
  - E.g.,
    - Gibbs sampler
    - Expectation-Maximization (EM) algorithm
    - Blahut algorithm
    - Dynamic programming, Viterbi algorithm

# Message-passing Method

- Design a (near) minimum-complexity algorithm that leverages the network structure to recursively solve a large-scale problem.
- E.g., belief propagation algorithm for inference on graphical models

# Approximation Algorithms for NP Hard Problems

- Exact algorithm:
  - computationally infeasible in practice
- Approximation algorithm:
  - achieves theoretically proven good performance, e.g., close to the optimal
  - Polynomial time but may have high complexity
- Heuristic algorithm:
  - lower complexity than approximation algorithm but no performance guarantee

# Compressive Sensing Approach for NP Hard Problems (1)

- Compressive sensing (CS) is a technique for acquiring and reconstructing a signal utilizing the prior knowledge that it is sparse or compressible.
- A new paradigm to avoid NP hardness
  - Convert a mixed-integer program to a nonlinear program
  - Solve the nonlinear program
  - Decoding: map the real-valued solution to integer valued feasible solution (a valid codeword)

# Compressive Sensing Approach for NP Hard Problems (2)

- CS = Model selection = penalized least squares
- We can apply CS to
  - the graph learning problem
  - parameter estimation problem of a large-scale network

# Joint Congestion Control and Scheduling in Ad Hoc Networks

Using Decomposition Principle

# Optimization in Ad-hoc network



Challenges in Ad-hoc:

Resource Allocation :

- Congestion Control
- Scheduling
- Efficiency/Fairness

QoS awareness

- Elastic (email)
- Inelastic (voice)

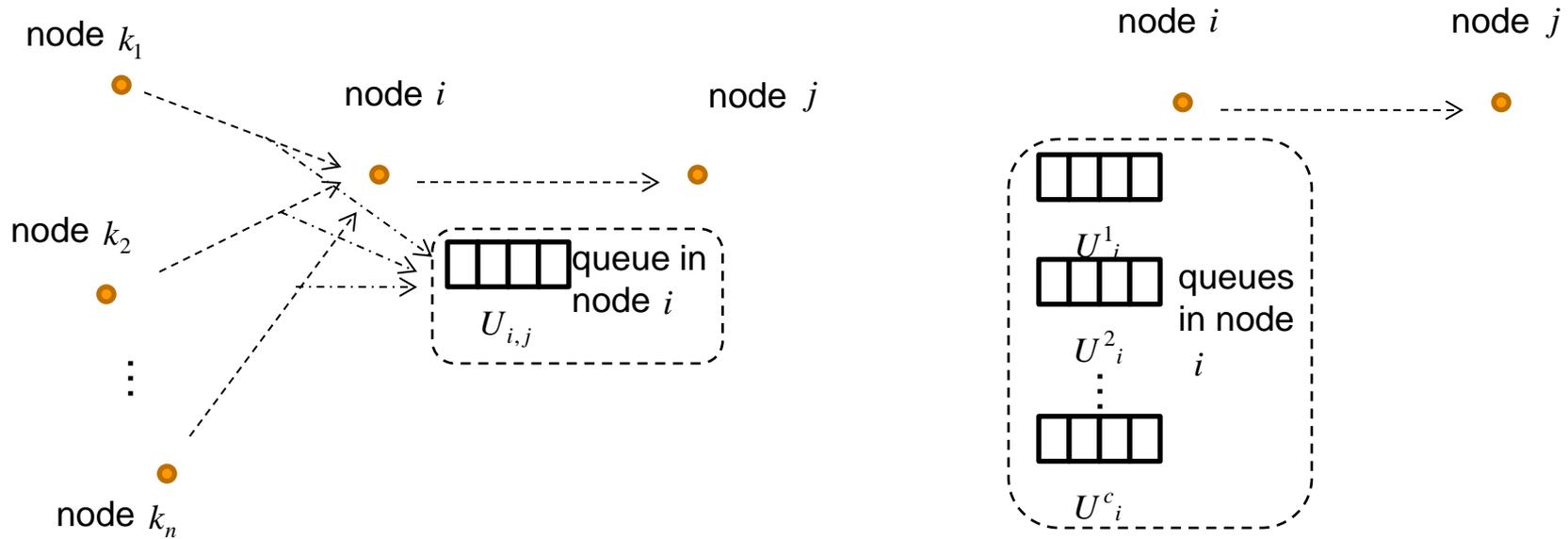
Decentralized algorithm needed:

- Less overhead
- Fast convergence

# Problems and Solutions

- Existing works:
  - Network Utility Maximization (NUM) problem[Kelly98]
    - Maximum Weight Scheduling [Tassiulas92]
    - Dynamic Routing and Power Control (DRPC) [Neely, 03]
  - Capacity region for per-destination queuing system [Neely03]
  - Decomposition between congestion control and scheduling [Lin04]  
[Chiang07]
- Our Solutions:
  - per-next-hop queuing system
    - Reducing queuing overhead
    - Extending the definition of conventional capacity region
  - Sliding Mode (SM) based controller in wireless network
    - Providing distributed iterative algorithm to optimization problem with a large number of constraints [Utkin92]  
[Lagoa04]

# Per-next-hop queues



## Per-destination queue (PDQ)

- Defined on nodes
- The number of queues in each node equals to the number of destinations

## Per-next-hop queue (PNHQ)

- Defined on links
- The number of queues in each node equals to the number of neighbors

# Problem Formulation

- The NUM problem in per-next-hop queuing system

$$\max_{\{\mathbf{x}, P\}} \sum_{s \in \Theta^f} U_s(x^s) \quad (5a)$$

$$s.t. : \mathbf{x} \in Co(\mathcal{R}) \quad (5b)$$

$$\sum_{s: b_s=i} x_{i,j}^s - R_{out(i,j)} + R_{in(i,j)} \leq 0, \forall i \in \Theta^n, j \in S_i \quad (5c)$$

$$P \in \mathcal{P} \quad (5d)$$

$$\mathbf{h} \leq 0 \quad (5e)$$

- The dual decomposition w.r.t. the flow conservation constraint

$$\begin{aligned} D(\Lambda) &= \max_{\{\mathbf{x}, P\}} \sum_{s \in \Theta^f} U_s(x^s) - \sum_{i \in \Theta^n, j \in S_i} \lambda_{i,j} \left( \sum_{s: b_s=i} x_{i,j}^s - R_{out(i,j)} + R_{in(i,j)} \right) \\ &= \max_{\{\mathbf{x}\}} \left( \sum_{s \in \Theta^f} U_s(x^s) - \sum_{i \in \Theta^n, j \in S_i} \lambda_{i,j} \sum_{s: b_s=i} x_{i,j}^s \right) + \max_{\{P\}} \sum_{i \in \Theta^n, j \in S_i} \lambda_{i,j} (R_{out(i,j)} - R_{in(i,j)}) \quad (6) \end{aligned}$$

# Solutions

- The congestion control problem

$$\max_{\{x \in Co(\mathcal{R}), h \leq 0\}} \left( \sum_{s \in \Theta^f} U_s(x^s) - \sum_{i \in \Theta^n, j \in S_i} \lambda_{i,j} \sum_{s: b^s=i} x_{i,j}^s \right) \quad (7)$$

- The scheduling problem

$$\max_{\{P \in \mathcal{P}\}} \sum_{i \in \Theta^n, j \in S_i} \lambda_{i,j} (R_{out(i,j)} - R_{in(i,j)}) \quad (8)$$

- The system governing law

$$\dot{\lambda}_{i,j}(t) = \left( \sum_{s: b^s=i} x_{i,j}^s(t) - R_{out(i,j)}(t) + R_{in(i,j)}(t) \right)_{\lambda_{i,j}(t)}^+ \quad (11)$$

$$\dot{x}_{i,j}^s(t) = \frac{\partial U_s(x^s)}{\partial x_{i,j}^s} \Big|_{x^s(t)} - \lambda_{i,j}(t) + \delta(t)u(x_{i,j}^s(t)) + \sum_{m \in H^s} v_m(t) \frac{\partial h_m(x^s)}{\partial x_{i,j}^s} \Big|_{x^s(t)} \quad (13)$$

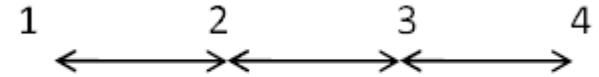
$$\hat{P}(t) = \arg \max_{P \in \mathcal{P}} \sum_{i \in \Theta^n, j \in S_i} \lambda_{i,j}(t) (R_{out(i,j)}(t) - R_{in(i,j)}(t)) \quad (16)$$

- We proved that (11), (13) and (16) converge to the optimal solutions if utility functions are concave

# Simulation and Results

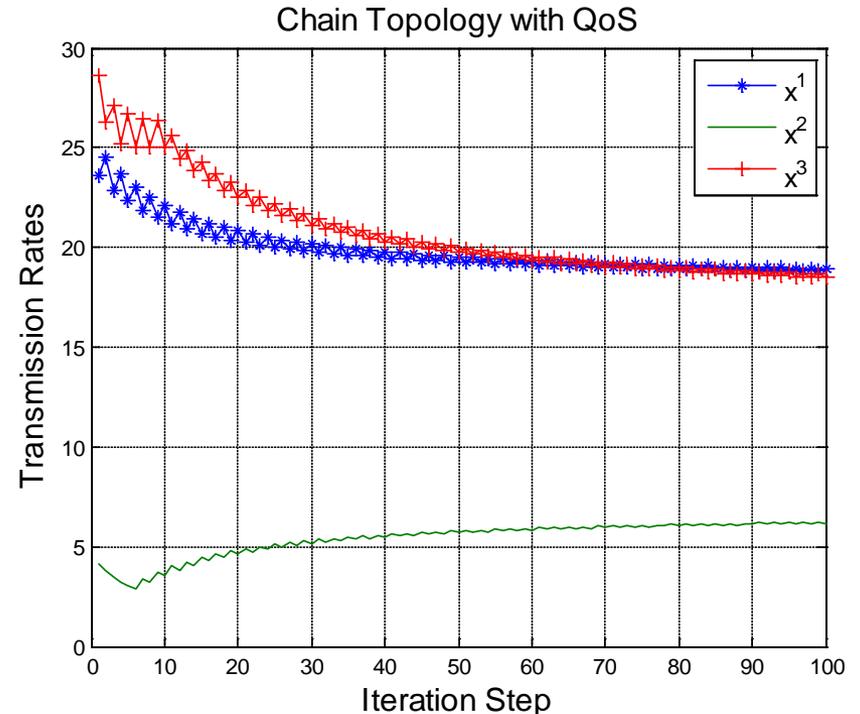
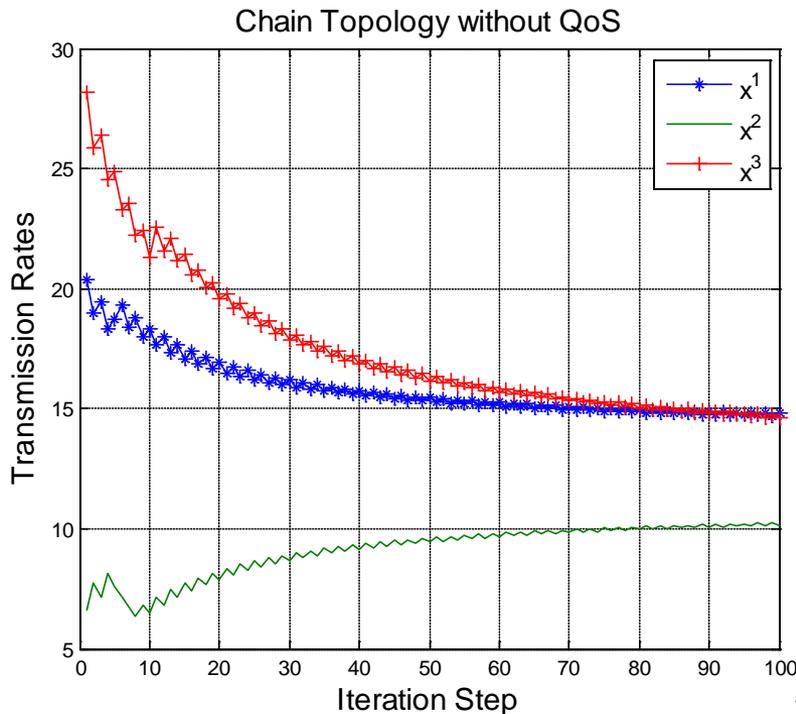
Chain topology:

- $l_{2,3}$  is a bottleneck in the network expected to be smaller;
- The QoS constraint on  $x^1$  can be satisfied



(a) Chain topology

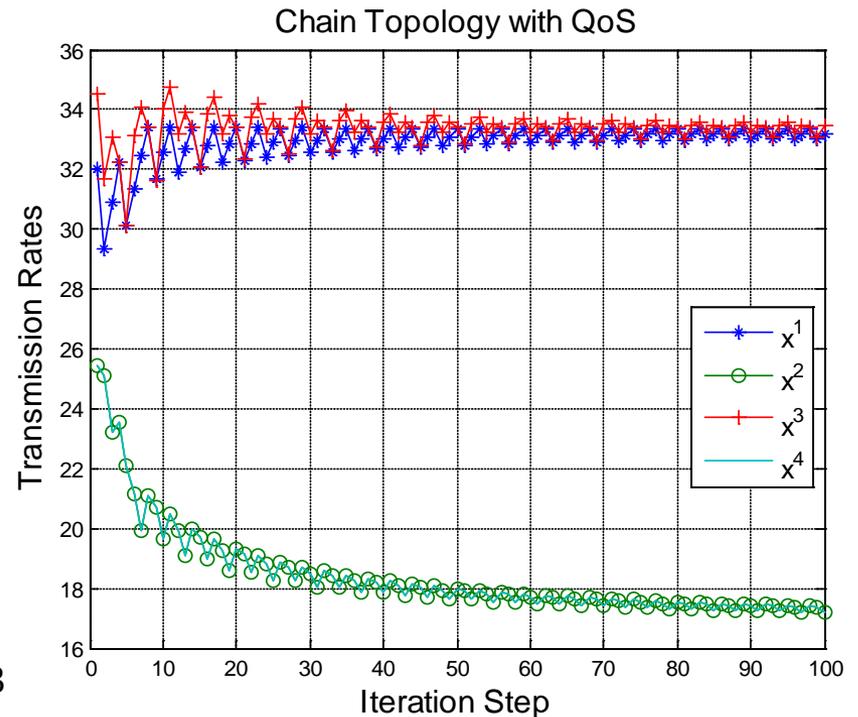
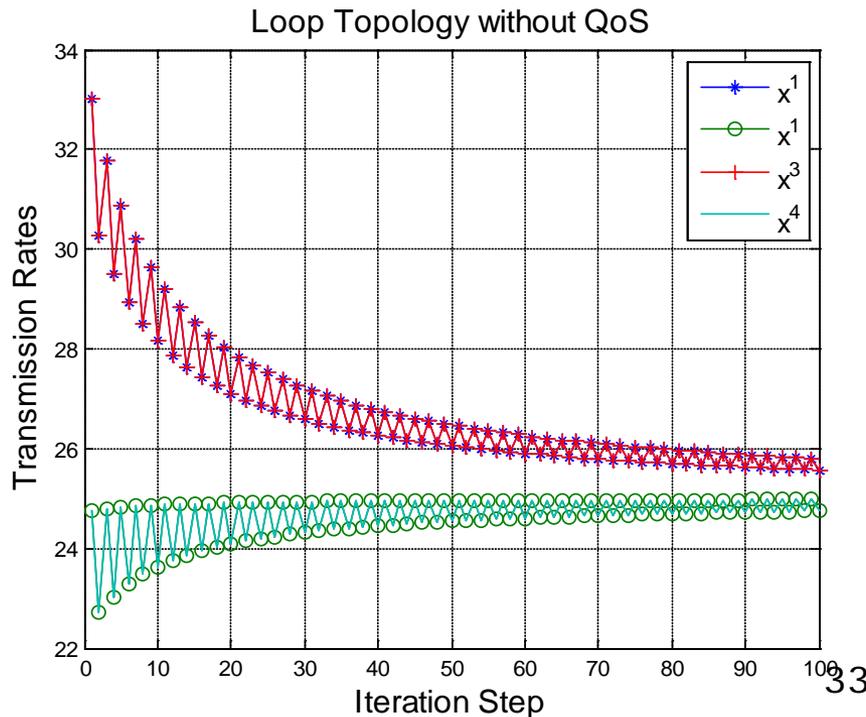
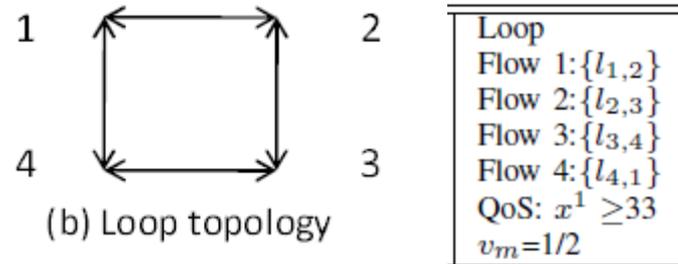
Chain
Flow 1: $\{l_{1,2}, l_{2,3}\}$
Flow 2: $\{l_{2,3}, l_{3,4}\}$
Flow 3: $\{l_{3,4}\}$
QoS: $x^1 \geq 18$
$v_m = 1/3$



# Results

Loop topology:

- The traffic is symmetric, so the transmission rates are also symmetric;
- The QoS constraint on  $x^1$  can be satisfied



# Conclusions

## Conclusions:

- Decomposition principle simplifies the NUM problem
- The per-next-hop queuing mechanism can reduce queuing overhead, compared to the per-destination queuing
- Network utility converges to the optimal
- The QoS constraints on transmission rates can be satisfied by sliding mode control

Thank you!