Distributed Resource Allocation in Wireless Networks

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Thesis Defense

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Outlines

1. **Background and Motivations**
2. **Distributed Resource Allocation in OFDM-based MAC**
3. **Distributed Cross-layer Resource Allocation in INs**
4. **Cross-layer Design for Dense INs**
5. **Conclusions and Future Works**

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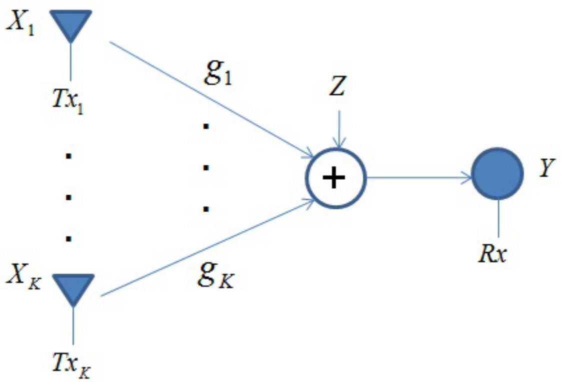
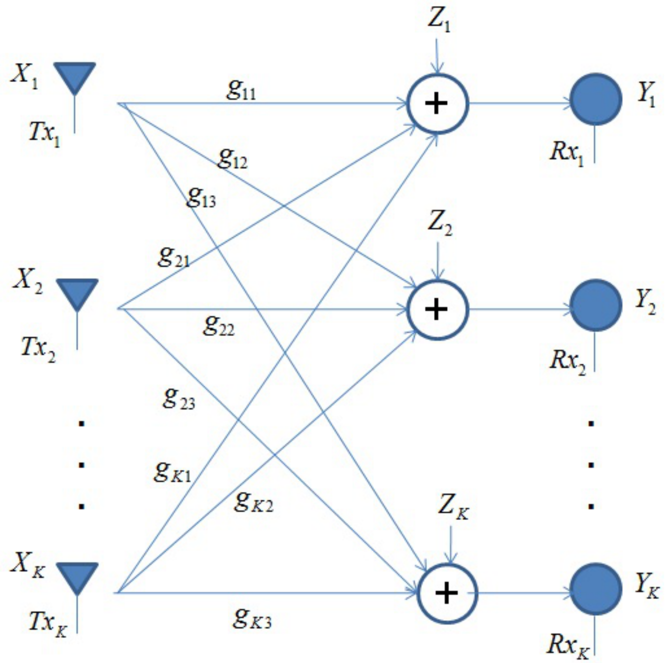
Multiuser Networks



Multiple Access Channel (MAC)

- **All messages will be decoded at a unique receiver**



Single-hop ad hoc network (Interference Network - IN)

- **Each source transmits to an intended receiver.**
- **Each receiver primarily decodes its information flows of interest. Other flows are eventually decoded only if beneficial.**

Resource Allocation in Wireless Networks

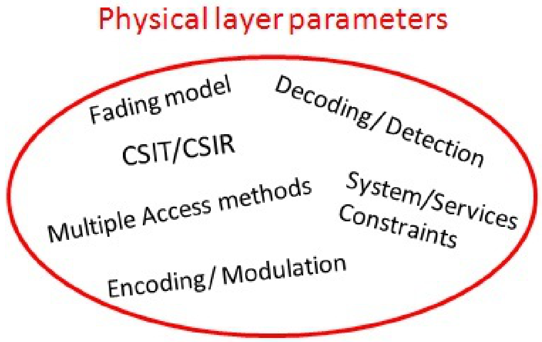
In a wireless network, users transmit by sharing resources, e.g. frequency spectrum, time, code, space, and adjusting their own resources and capabilities, e.g., power, transmission rate.

Resource allocation defines the distribution and use of shared and individual resources with the goal of optimizing individual or global performance while considering the users' limits and requirements.

At the Physical Layer

Theory of saturated queues, i.e., sources transmit seamlessly.

- Essential assumptions:



- On the channels
  - Type of fading (slow/fast, frequency selective/flat), multiple access methods.
  - Channel Side Information (CSI) at the transmitters and receivers.
- On the transmitter
  - Encoding/modulation methods.
  - System/service constraints, e.g., power constraint, max outage probability.
- On the receiver
  - Detection/decoding methods.

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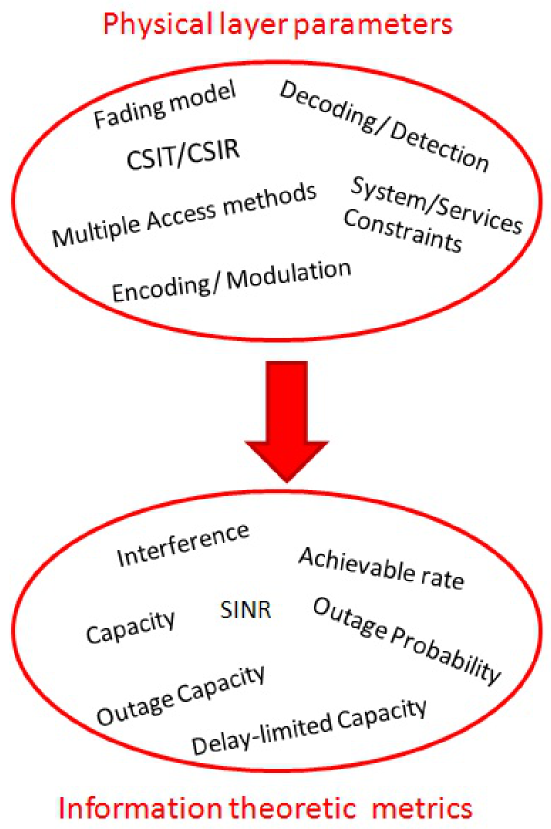

IT Assumptions and Performance Metrics (1)

- **Ergodic capacity (Shamai et al. 95): Convenient for fast-fading, with no CSI at the transmitters.**

- **Throughput capacity (Tse. et al. 98): Convenient for fast-fading channels with full CSI at the transmitter.**

- **Delay-limited (zero-outage) capacity (Hanly et al. 98): Convenient for slow-fading channels with full CSI at the transmitters.**
  - **Intersection of max achievable rate regions for all possible channel states.**
  - **Limited delay: channel non-ergodic during codeword transmission.**
  - **Large power budget is required to compensate all possible levels of fading and interference.**

Performance metrics in slow-fading channels

What for slow-fading channels with no or partial CSIT?

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Outage event is unavoidable!

- **Outage Capacity:**
  - **Transmission at constant rate across all unknown fading states, accepting some outage probability.**
  - **Max transmission rates region with outage probability not greater than a given threshold.**
  - **Joint rate and power allocation.**

Why Slow Fading?

- **Scenarios with partial CSI at the transmitters have been thoroughly studied. In contrast, many systems with no/partial CSI at the transmitter and slow-fading channels are not well understood.**
- **Slow-fading systems are relevant in practice since they are typical of services with low delay tolerance.**

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We focus on slow-fading scenarios.

Challenges of RA in Multiuser Networks (1)

- **Full CSIT in multiuser networks require a large bandwidth for the feedback channel. In interference networks the feedback grows exponentialy with the number of users. $\rightarrow$ Very costly in terms of feedback load.**
- **Optimum considered resource allocation have a complexity that scales exponentially with the number of users. $\rightarrow$ Very costly in terms of computational complexity.**
- **Scalability problem.**

Challenges of RA in Multiuser Networks (2)

Strategic direction to solve these challenges:

- **Limit the knowledge on the channel state to reduce signaling and improve scalability.**
- **Use distributed resource allocation algorithms to reduce complexity and improve scalability.**

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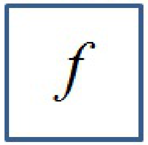
We study distributed resource allocation with partial CSI at the transmitters!

Centralized vs. Distributed Resource Allocation

Centralized



$$\max \quad f(\underline{x})$$
$$s.t. \quad \underline{x} \in \underline{X}$$

Centralized vs. Distributed Resource Allocation

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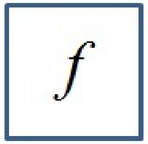

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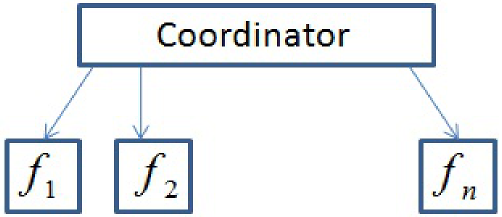
Decentralized



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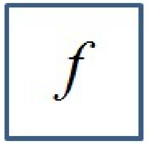

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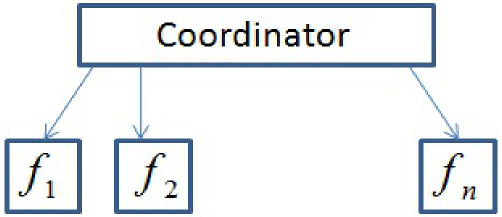

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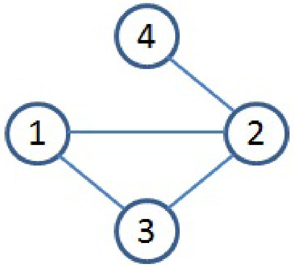
Cooperative Distributed



$$\max_{x_v} \quad \sum_v f_v(\underline{x}, \theta)$$
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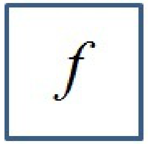

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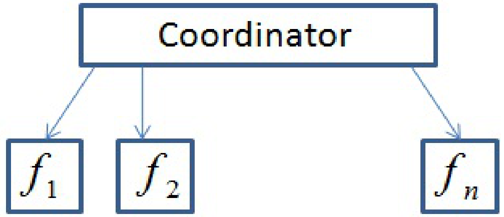

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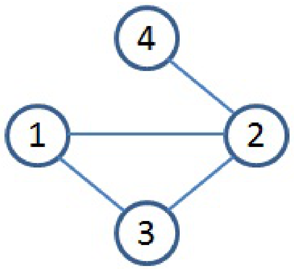

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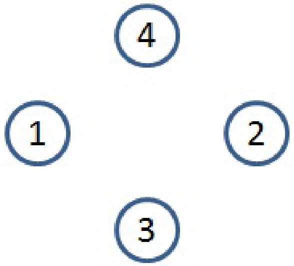
Non-cooperative Game



$$\max_{x_v} \quad \{f_v(\underline{x})\}_{v \in V}$$
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Centralized vs. Distributed Resource Allocation

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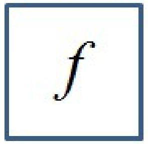

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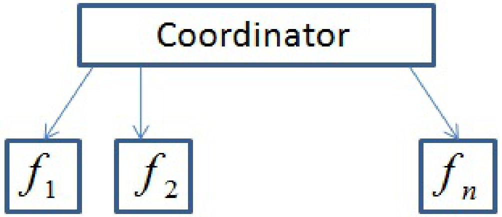

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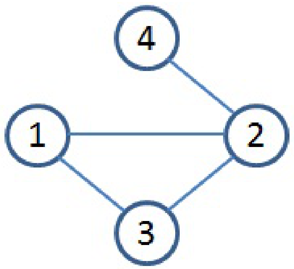

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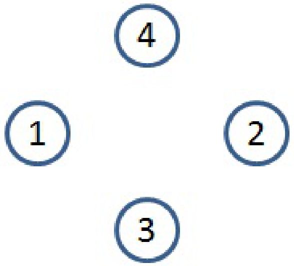

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- **Network structure and level of information on the state of network.**
- **Analytical complexity.**
- **Optimality: global, local, NE.**

Limitations of Saturated Queue Approach

The "saturated queue" approach breaks down when user/traffic dynamics must be considered!

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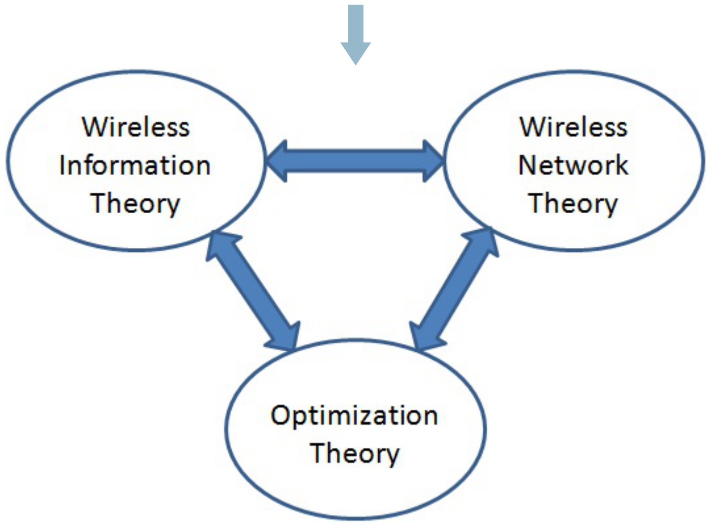

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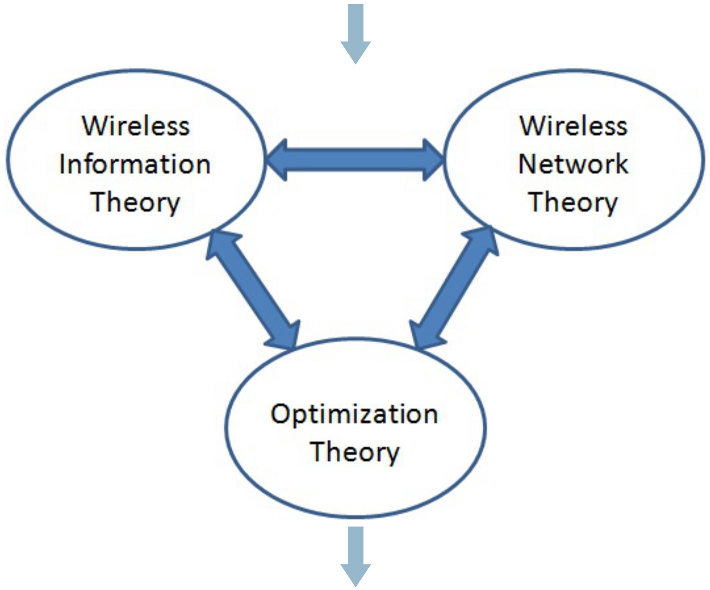

Cross-layer approach is required!

A cross-layer approach promises remarkable improvements in performance.

Objectives of my research work

- Understand the impact of different levels of CSIT on the design and optimality of resource allocations.
- Analyze the trade-off between performance and complexity of centralized and distributed approaches in an interference limited network.
- Design distributed joint rate and power allocation algorithms in a slow-fading network with partial CSIT, considering an average power constraint.
- Propose cross-layer design of distributed control mechanisms, scheduling, and admission control in an interference network, considering relevant constraints on average power, average queue length, and max tolerable outage probability.

Considered Scenarios

- **Saturated queue approach in:**
  - **OFDM-based MAC**
- **Cross-layer approach in:**
  - **Finite INs**
  - **Dense INs**

Outlines

Background in Centralized and Distributed Approaches

- Optimization of Centralized power allocation based on full CSIT and capacity C.

  Complexity exponential in the number of users K and subcarriers N!

  As $N \to \infty$, complexity becomes linear in N via duality (Yu 2006)

- Distributed power allocation based on partial [a] CSIT, fast fading via Bayesian games (He et al. 2008)

  Powers optimized simultaneously

  $\mathrm{E}_{\boldsymbol{g}_2}\{C_1|\boldsymbol{g}_1\}$ and $\mathrm{E}_{\boldsymbol{g}_1}\{C_2|\boldsymbol{g}_2\}$

Figures of Merit

for $K = 2$ usrs and N subcarriers

User 1 Achievable Rate

$$C_1 = \sum_{n=1}^{N} \ln\left(1 + \frac{P_1^n g_1^n}{N_0 + P_2^n g_2^n}\right)$$

Total Achievable Rate

$$C = C_1 + C_2$$

[a] Exact knowledge of the own channel and statistical knowledge of other channels.

System Characteristics

- **Quasistatic fading**
- **Partial channel state information at the transmitter**

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Outage event if transmit rate exceeds capacity

$$\underbrace{R_i^n}_{\text{Transmit Rate}} > \underbrace{\log\left(1+\frac{P_i^n g_i^n}{N_0+P_j^n g_j^n}\right)}_{\text{Capacity}}$$

Throughput: average information reliably received

$$T_i(\boldsymbol{P}_i, \boldsymbol{R}_i, \boldsymbol{P}_j, \boldsymbol{R}_j) = \sum_{n=1}^{N} R_i^n \Pr\left\{R_i^n \leq \log\left(1+\frac{P_i^n g_i^n}{N_0+P_j^n g_i^n}\right)\right\}$$

Optimum Joint Allocation in Slow Fading with Partial CSI

- **Allocate jointly rates and powers to maximize the total throughput**

$$u(\boldsymbol{P}_1, \boldsymbol{R}_1, \boldsymbol{P}_2, \boldsymbol{R}_2) = \underbrace{\mathrm{E}_{\boldsymbol{g}_1}(T_1(\boldsymbol{P}_1, \boldsymbol{R}_1, \boldsymbol{P}_2, \boldsymbol{R}_2))}_{\substack{\text{Average Throughput} \\ \text{User}1}} + \underbrace{\mathrm{E}_{\boldsymbol{g}_2}(T_2(\boldsymbol{P}_2, \boldsymbol{R}_2, \boldsymbol{P}_1, \boldsymbol{R}_1))}_{\substack{\text{Average Throughput} \\ \text{User}2}}$$

under a maximum power constraint for each user,

$$\sum_{n=1}^{N} P_k^n \leq \overline{P}_k;$$

- **Distributed approach**

Exponential complexity in the number of users and subcarriers!

Reducing Complexity via Duality

We extend the results by Yu (2006) to throughput:

For $N \to \infty$, complexity become linear in N !

Two-Level Optimization

1st Level: For each subcarrier n find $(P_1^{n*}, R_1^{n*}, P_2^{n*}, R_2^{n*})$ parametric in λ_1 and λ_2 maximizing

$$g^n(P_1^n, R_1^n, P_2^n, R_2^n, \lambda_1, \lambda_2) = \underbrace{\mathrm{E}(T^n(P_1^n, R_1^n, P_2^n, R_2^n))}_{\text{average throughput subcarrier } n} - \underbrace{\lambda_1 P_1^n}_{\text{power cost user 1}} - \underbrace{\lambda_2 P_2^n}_{\text{power cost user 2}}$$

2nd Level: Minimization in λ_1 and λ_2 of

$$g^n(\boldsymbol{P}_1^*, \boldsymbol{R}_1^*, \boldsymbol{P}_2^*, \boldsymbol{R}_2^*, \lambda_1, \lambda_2) = \sum_{n=1}^{N} g^n(P_1^{n*}, R_1^{n*}, P_2^{n*}, R_2^{n*}, \lambda_1, \lambda_2)$$

Reducing Complexity via Bayesian Games

Complexity of the fist level still unaffordable!

Game theoretic approach to reduce complexity!

Two-Level Bayesian Game

User k aims at minimizing its cost

$$c_k(\lambda_1, \lambda_2) = \max_{\boldsymbol{R}_k, \boldsymbol{P}_k} \underbrace{\mathrm{E}_{\boldsymbol{g}_k} \left\{ T_k(\boldsymbol{R}_k, \boldsymbol{P}_k, \boldsymbol{R}_\ell, \boldsymbol{P}_\ell) - \lambda_k \sum_n P_k^n \right\}}_{\text{utility of user } k}$$

to achieve a maximum utility by properly setting its unit cost λ_k

Remark: In general the Nash equilibria of this game do not coincide with the constrained Bayesian game having the average throughput $\mathrm{E}_{\boldsymbol{g}_k} T_k(\boldsymbol{R}_k, \boldsymbol{P}_k, \boldsymbol{R}_\ell, \boldsymbol{P}_\ell)$ as utility function.

Two-Level Game Decomposition

Power and rate allocation $(\boldsymbol{R}_1^*(\lambda_1^*, \lambda_2^*), \boldsymbol{P}_1^*(\lambda_1^*, \lambda_2^*), \boldsymbol{R}_2^*(\lambda_1^*, \lambda_2), \boldsymbol{P}_2^*(\lambda_1^*, \lambda_2^*))$

2nd level game

Unit cost allocation λ_1^* and λ_2^* determined as Nash equilibrium

$$c_1(\lambda_1^*, \lambda_2^*) \leq c_1(\lambda_1, \lambda_2^*), \qquad \forall \lambda_1$$

$$c_2(\lambda_2^*, \lambda_1^*) \leq c_2(\lambda_2, \lambda_1^*), \qquad \forall \lambda_2$$

$(\boldsymbol{R}_1^*(\lambda_1, \lambda_2), \boldsymbol{P}_1^*(\lambda_1, \lambda_2), \boldsymbol{R}_2^*(\lambda_1, \lambda_2), \boldsymbol{P}_2^*(\lambda_1, \lambda_2))$

1st level game

Power and rate allocation parametric in λ_1 and λ_2 obtained as Nash equilibrium

$$\mathrm{E}(T_1(\boldsymbol{R}_1^*, \boldsymbol{P}_1^*, \boldsymbol{R}_2^*, \boldsymbol{P}_2^*) - \lambda_1 \sum_n P_1^{n*}) \geq \mathrm{E}(T_1(\boldsymbol{R}_1, \boldsymbol{P}_1, \boldsymbol{R}_2^*, \boldsymbol{P}_2^*) - \lambda_1 \sum P_1^n), \qquad \forall \boldsymbol{P}_1, \boldsymbol{R}_1$$

$$\mathrm{E}(T_2(\boldsymbol{R}_2^*, \boldsymbol{P}_2^*, \boldsymbol{R}_1^*, \boldsymbol{P}_1^*) - \lambda_2 \sum_n P_2^{n*}) \geq \mathrm{E}(T_2(\boldsymbol{R}_2, \boldsymbol{P}_2, \boldsymbol{R}_1^*, \boldsymbol{P}_1^*) - \lambda_2 \sum P_2^n), \qquad \forall \boldsymbol{P}_2, \boldsymbol{R}_2$$

Global Game

- **The throughput $T_k(\boldsymbol{R}_1, \boldsymbol{P}_1, \boldsymbol{R}_2, \boldsymbol{P}_2)$ is a piecewise function:**

  ⇓

  For each piece we consider a two-level game.

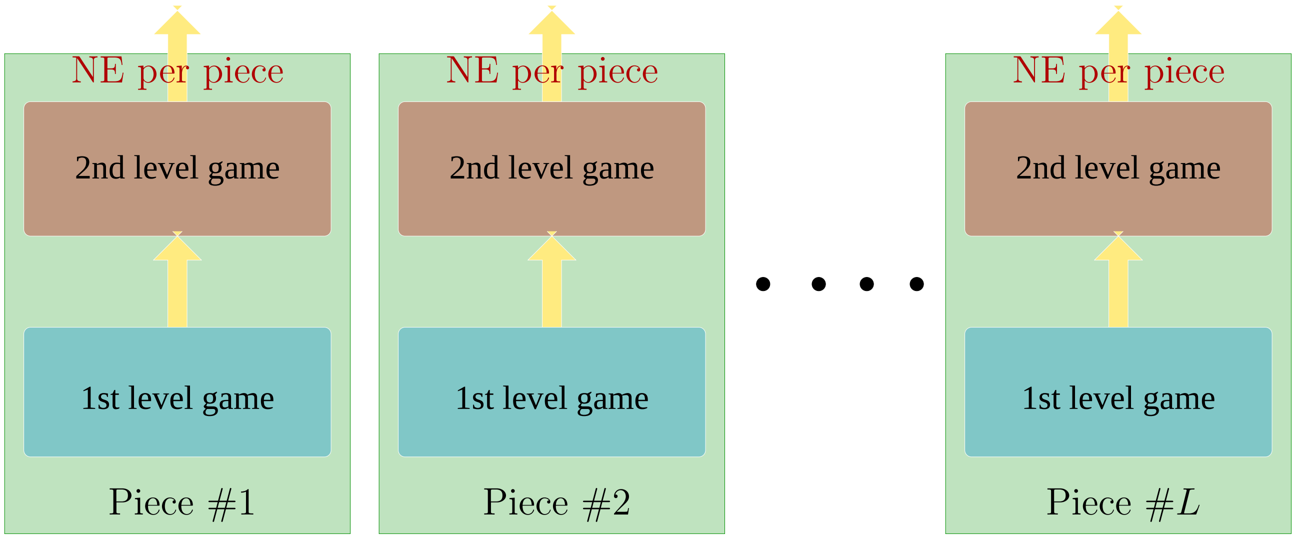
Global Game

- **The throughput $T_k(\boldsymbol{R}_1, \boldsymbol{P}_1, \boldsymbol{R}_2, \boldsymbol{P}_2)$ is a piecewise function:**

  For each piece we consider a two-level game.

- **The two-level game in each piece is submodular and NEs exist**

  Algorithm to determine all NEs in a piece



Global Game

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  For each piece we consider a two-level game.

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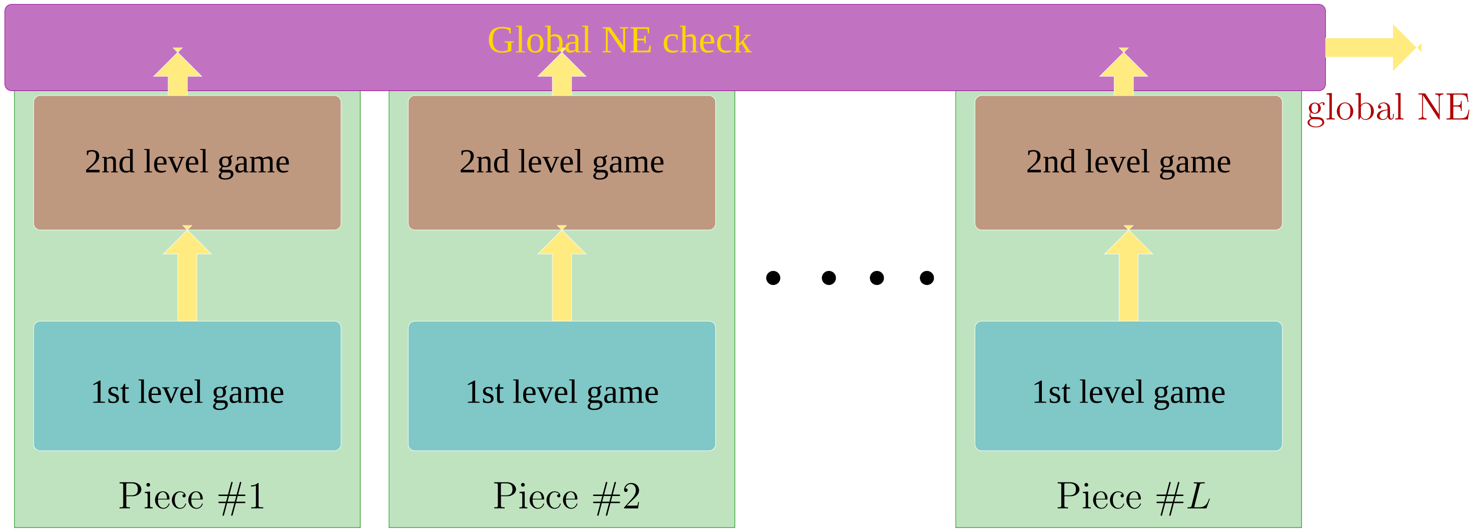
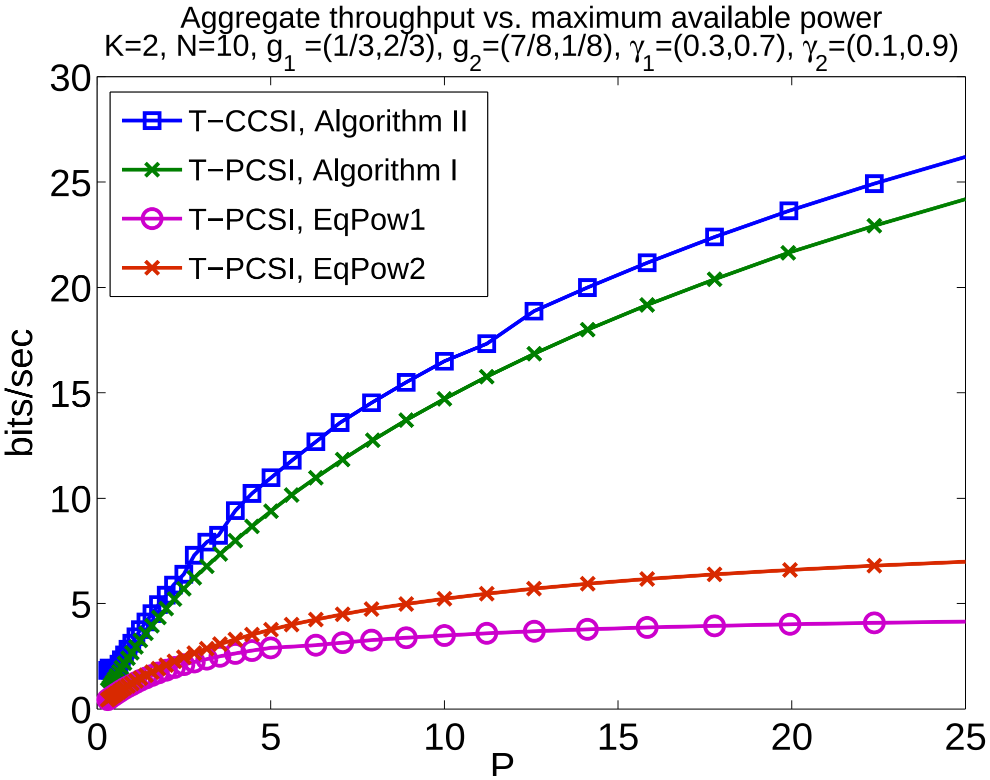
  Algorithm to determine all NEs in a piece

- Select among all possible NEs per piece the ones that are NE also for the global game



Nash Equilibrium vs Other Approaches



- **Setting:** $g_1 = \left\{\frac{1}{3}, \frac{2}{3}\right\}$; $\Pr\{g_1\} = \left\{\frac{3}{10}, \frac{7}{10}\right\}$
  $g_2 = \left\{\frac{7}{8}, \frac{1}{8}\right\}$; $\Pr\{g_1\} = \{0.1, 0.9\}$
  $N = 10, \ \overline{P}_1 = \overline{P}_2 = P$
- **Optimization based on full channel knowledge but yielding to a local minimum**
- **Allocation EqPow1 based on uniform power distribution without outage;**
- **Allocation EqPow2 based on uniform power distribution with outage;**
- **The NE curve follows closely the optimization performance with complete CSI**
- **Uniform power allocations implies a remarkable loss in performance.**

Summary, Remarks, and Observations

- **Joint rate and power allocation in slow fading systems with partial state information based on Nash equilibria.**
- **Low complexity algorithm as $N \to +\infty$ able to determine all Nash equilibria if they exist. In contrast, the optimization for partial CSI with affordable complexity is still an open problem.**
- **A Nash equilibrium selection criterium needs to be enforced because of multiple Nash equilibria.**

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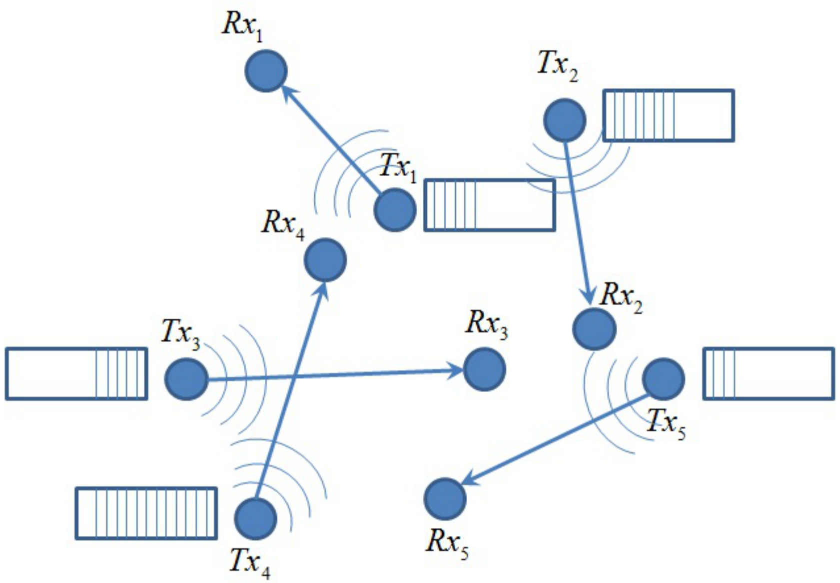
Problem Statement

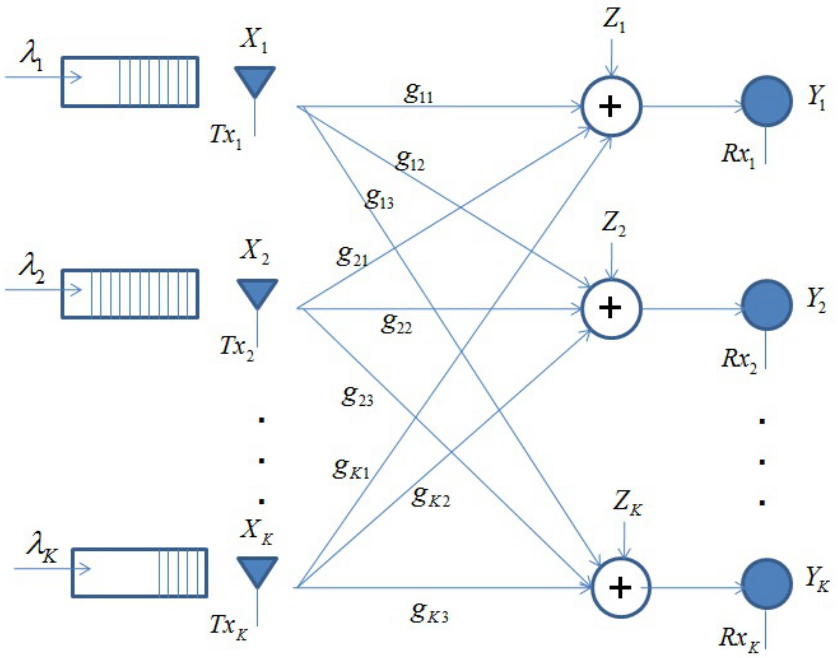
- Distinct transmitters and receivers
- Single-hop ad hoc network



Devise control mechanisms that:

- **Supports the self-forming and self-haling properties of ad hoc networks → Distributed algorithm.**
- **Is appropriate for slow-fading channels, assuming partial knowledge of states of other communication pairs → Throughput maximization, joint power and rate allocation.**
- **Takes into account traffic dynamics → Cross-layer approach considering queues dynamics.**
- **Guarantees the network stability → Finite length buffers and admission control mechanisms.**

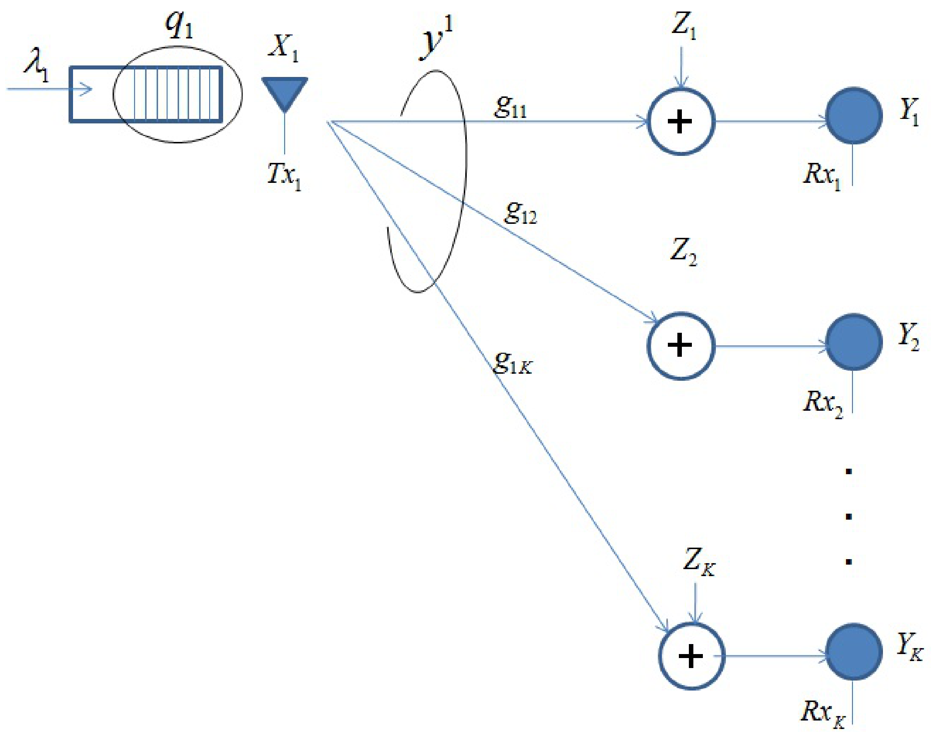
System Model



- **Arrival process at node k follows an i.i.d. distribution with average rate λ_k.**
- **The evolution of the average power attenuation over each link is an ergodic Markov chain.**
- **State and action sets have finite cardinalities.**

How does the user decide?

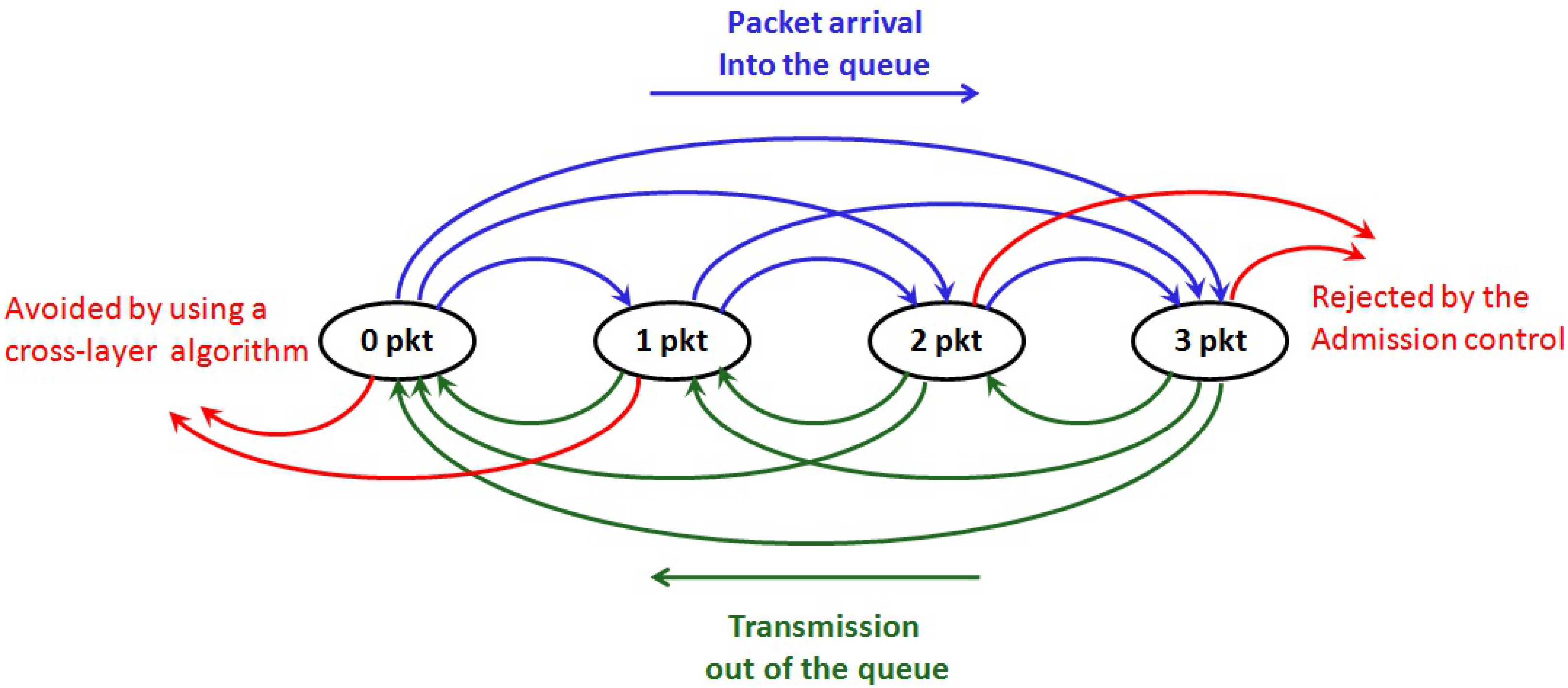
States (x_k):



Decisions (a_k):

- **When to transmit?**
- **How to transmit (power and rate)?**
- **Accept/Reject?**

Intended Effect of Decisions on Queue Dynamics



Remark: The transition probability of the Markov chain depends on the transmitter's policies (Markov Decision Process)

Optimum Joint Power and Rate Allocation

- **Maximizing the expected throughput:**

$$\mathbb{E}_{x_k} \max_{(p_k(x_k),\mu_k(x_k))} \left[\Pr\{ r_k(\; x^k(t) \; , \underbrace{(p_k, p_{-k})}_{\text{Power all users}} \;) \geq \underbrace{\mu_k(t) R}_{\text{Rate user } k} \; \} \mu_k(t) R \right]$$

- **Under constraints on:**

Average Power: $\mathbb{E}_{x_k}\left[p_k(x_k(t))\right] \leq \overline{p}_k$

Average Buffer Length: $\mathbb{E}_{x_k}\left[q_k(t)\right] \leq \overline{q}_k$

Probability of Outage at Steady State: $\mathbf{Pr}\{r_k(x_k(t), \boldsymbol{p}) < \mu_k(t) R_k(t)\} \leq \overline{P}_k^{out}, \forall (x_k, a_k)$

Optimum Joint Power and Rate Allocation

- **Maximizing the expected throughput:**

$$\mathbb{E}_{x_k} \max_{(p_k(x_k),\mu_k(x_k))} \left[\Pr\{ r_k(\ x^k(t) \ , \underbrace{(p_k, p_{-k})}_{\substack{\text{Power} \\ \text{all users}}} \ ) \geq \underbrace{\mu_k(t)R}_{\substack{\text{Rate} \\ \text{user } k}} \ \} \mu_k(t)R \right]$$

- **Under constraints on:**

Average Power: $\mathbb{E}_{x_k}\left[p_k(x_k(t))\right] \leq \overline{p}_k$

Average Buffer Length: $\mathbb{E}_{x_k}\left[q_k(t)\right] \leq \overline{q}_k$

Probability of Outage at Steady State: $\mathbf{Pr}\{r_k(x_k(t), \boldsymbol{p}) < \mu_k(t)R_k(t)\} \leq \overline{P}_k^{out}, \forall (x_k, a_k)$

Exponential complexity in the number of users and the cardinality of their state and action sets!

Reducing Complexity Via Stochastic Games

By formulating the problem as stochastic game, the solutions can be obtained through an iterative linear programming.

⬇

Linear complexity in mixed strategies of the users!

Formulation as an Stochastic Game

- **A mixed strategy $z_k(x_k, a_k)$ is the joint probability that transmitter k performs action a_k while being in state x_k (i.e. probability of $< x_k, a_k >_{n_k}, n_k \in \{1, ..., g_k\}$).**
- **Expected throughput as a multilinear function of mixed strategies:**

$$\rho_k = \underbrace{\sum_{n_1=1}^{g_1} \sum_{n_2=1}^{g_2} ... \sum_{n_K=1}^{g_K}}_{\text{Average over the strategies of all users}} \quad \underbrace{c^{(k)}_{n_1 n_2 ... n_K}}_{\text{Throughput at fixed strategies } n_j, j=1,...,K} \quad \underbrace{z_1^{n_1} z_2^{n_2} ... z_K^{n_K}}_{\text{Mixed strategies of all users}}$$

- **All constraints of transmitter k can also be presented as linear function of mixed strategies of user k.**

Game Formulations

- **Players**
  - **Selfish**: the coefficients $c^{(k)}_{n_1,n_2...n_K}$ account only for the throughput of user k.
  - **Cooperative**: the coefficients $c^{(k)}_{n_1,n_2...n_K}$ account for the aggregate throughput.
- **The individual/ aggregate throughputs depend on the decoders at the receivers:**
  - **Single User - SU**
  - **Successive Interference Cancelation - SIC**

Game Players / Decoder	Selfish	Cooperative
Single User decoder	A-self-SU	A-Coop-SU
Successive Interference Cancellation	A-self-SIC	A-Coop-SIC

Game Solutions (Nash Equilibria)

The existence of NE for general class of constraint stochastic games, where players have independent state processes is proven in [Altman,2006].

In general, systems with SIC decoders have more than a Nash equilibrium!

Best Response

Best response to the optimal policies of the others reduces to Linear Programming-LP.

In a symmetric network the BR converges to NE points.

Numerical Results: Effect of Cross-layer Design

- **Single solution for SU, multiple solutions for SIC.**
- **SIC transfer more or equal packets with less or equal power.**
- **Drop rate significantly improves using out cross-layer approach.**

Throughput improves between 20% and 68%

Drop rate decreases significantly using throughput as metrics

		Throughput	Drop rate
SU	A-self-SU	0.49	0.15
SU	A-Coop-SU	0.5	0.17
SIC	A-self-SIC1	0.64	0.16
SIC	A-self-SIC2	0.69	0.15
	[Altman et al. 07]	0.41	0.37

Benchmark [Altman et al. 07]: Heuristic performance metric based on Ergodic capacity, and only power allocation.

(i) Arrival process: Poisson distribution with average rate $\lambda_k = 1$, (ii) CS varies according to a Markov chain with equal probability of keeping the state or changing to adjacent channel gain levels, (iii) Buffer states $= \{0, ..., 5\}$, Channel states $= \{0, ..., 2\}$, Power levels $= \{0, ..., 3\}$, Possible rates $= \{0, ..., 5\}$, $\bar{R} = 1$.

Summary, Remarks, and Observaitons

- Distributed algorithms for joint power and rate allocation and admission control aiming at maximizing the individual throughput.
- Using discrete sets of states and actions the utility function yields a stochastic game with a multilinear function on the probability of state and action pairs.
  - The existance of NE is proved based on the properties of LP.
  - Based on the multilinear characteristic of the utility function, a best response algorithm is proposed. BR algorithm converges to NE in a symmetric network.
- Our cross-layer approach has remarkable performance improvements comparing to the models neglecting the queue dynamics or the probability of outage events.

Outlines

1. Background and Motivations
2. Distributed Resource Allocation in OFDM-based MAC
3. Distributed Cross-layer Resource Allocation in INs
4. **Cross-layer Design for Dense INs**
5. Conclusions and Future Works

Motivations

The previous cross-layer algorithm has a high complexity when the number of users or the cardinality of state and action sets increase. Its complexity is unaffordable in dense networks.

However, in dense interference networks the effects of interferers tend to deterministic limits!

⇓

The complexity of the problem can be reduced.

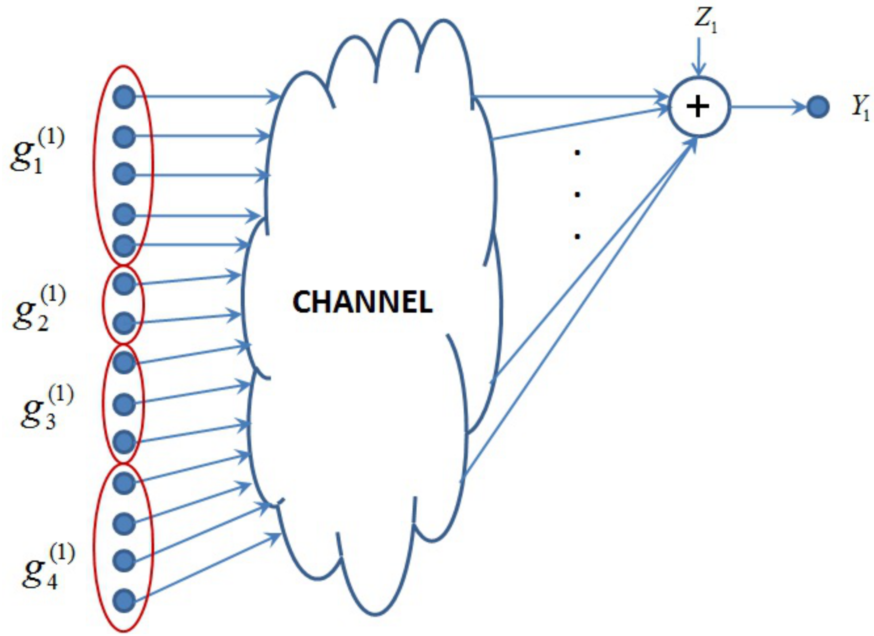
Extra Assumptions and Relevant Properties

- **Link between a source and a destination is an N-dimensional vector channel with identical statistics over all N paths.**
- **For dense networks, we determine the strategies assuming $K, N \to \infty$ with $\frac{K}{N} \to \beta > 0$, and applying use of random matrix theory**

Relevant Properties:

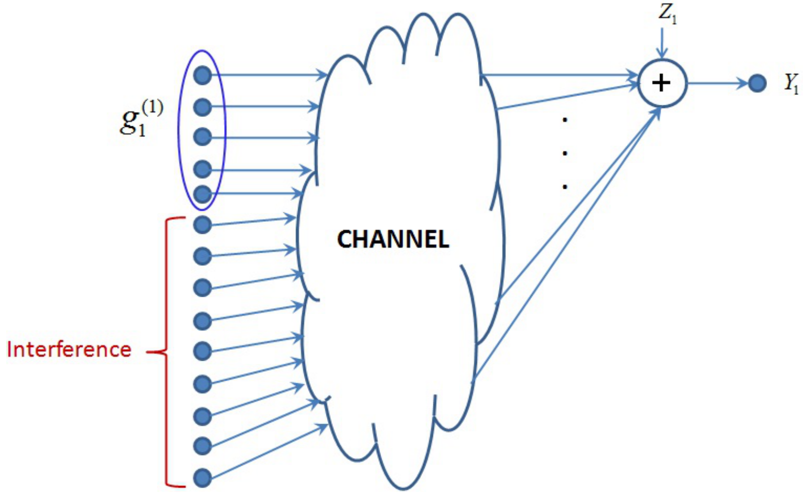
- **In dense interference networks the effect of random channels tends to deterministic limits.**
- **Given a receiver k, the group m of transmitters n having the same receiver power p_m^k and the same transmitting rate μ_m^k is g_m^k.**

$$g_m^{(i)} : \left\{ n \in \{1, ..., K\} | (p_n^i, \mu_n^i) = (p_m^i, \mu_m^i) \right\} .$$

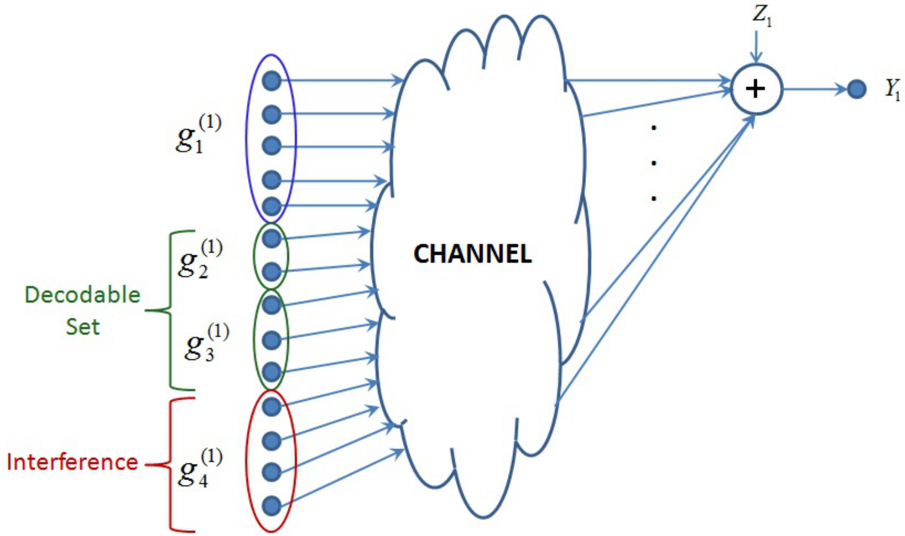


Single/Multi Group Decoder

Single Group Decoder:



Multi Group Decoder:



Receiver

We consider different receivers depending on the assumptions we make about:

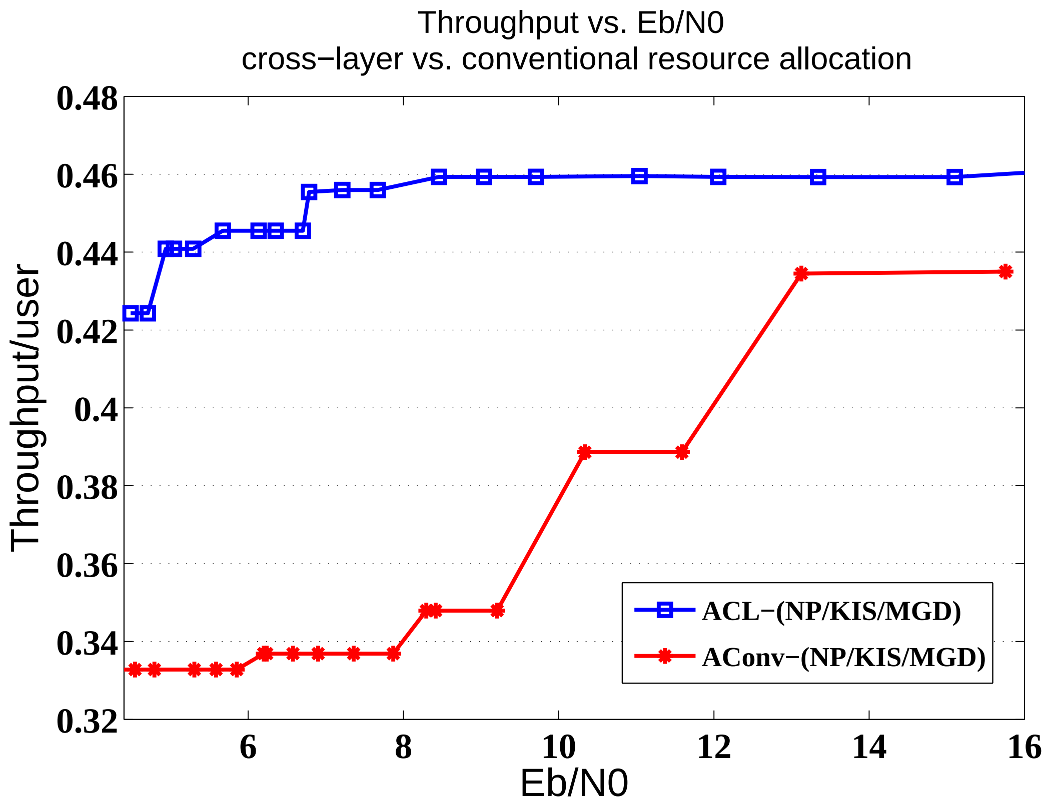
- **The level of the information about interference structure available at the receivers.**
- **Use of suboptimal receivers based on preliminary pre-decoding processing (e.g. multiuser detection) followed by decoding.**
- **Type of decoder: single/multi group decoder.**

- **KIS: Known Interference Structure**
- **UIS: Unknown Interference Structure**
- **SGD: Single Group Decoding**
- **MGD: Multi Group Decoding**

Cases under study

	MMSE	No Pre-processing
KIS	------	SGD/MGD
UIS	SGD	SGD

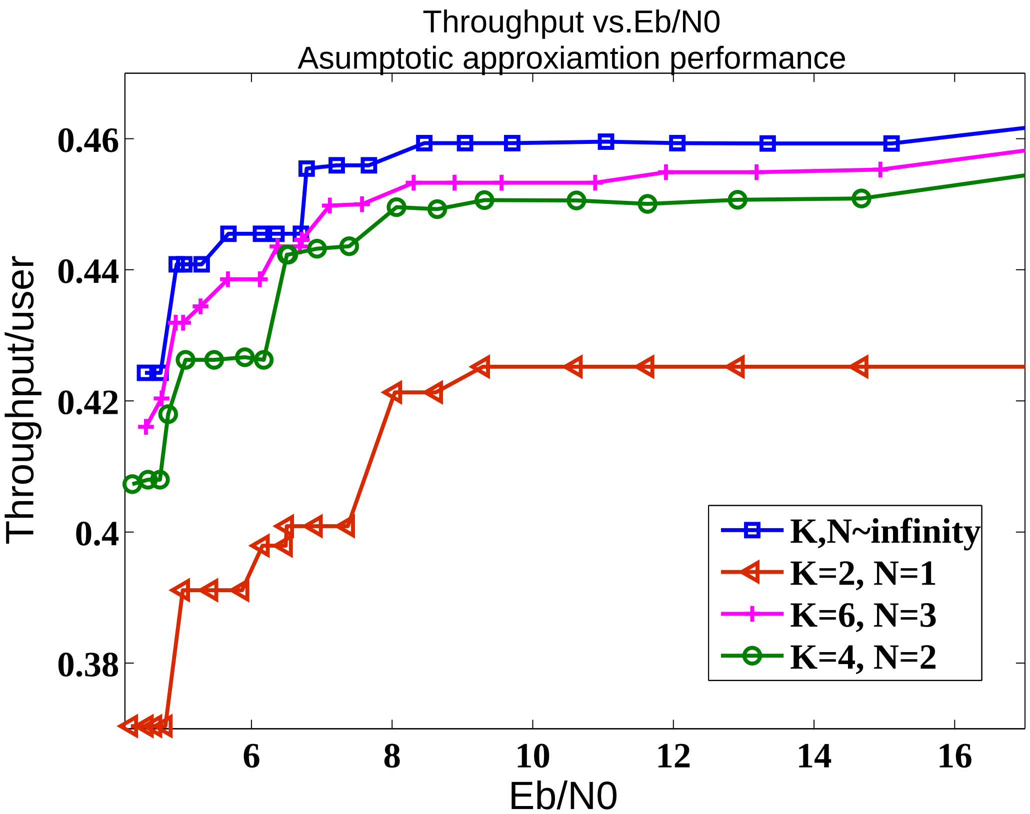
Numerical Results: Cross-layer vs. Conventional



- **In the conventional approach more power is consumed for sending a given packet.**
- **There are cases where power is adjusted to satisfy a rate while there is not enough data in the queue.**

(i) Arrival process: Poisson distribution with average rate $\lambda_k = 1$, (ii) CS varies according to a Markov chain with equal probability of keeping the state or changing to adjacent channel gain levels, (iii) Buffer states $= \{0, ..., 5\}$, Channel states $= \{0, ..., 2\}$, Power levels $= \{0, ..., 3\}$, Possible rates $= \{0, ..., 5\}$, $R = 1$.

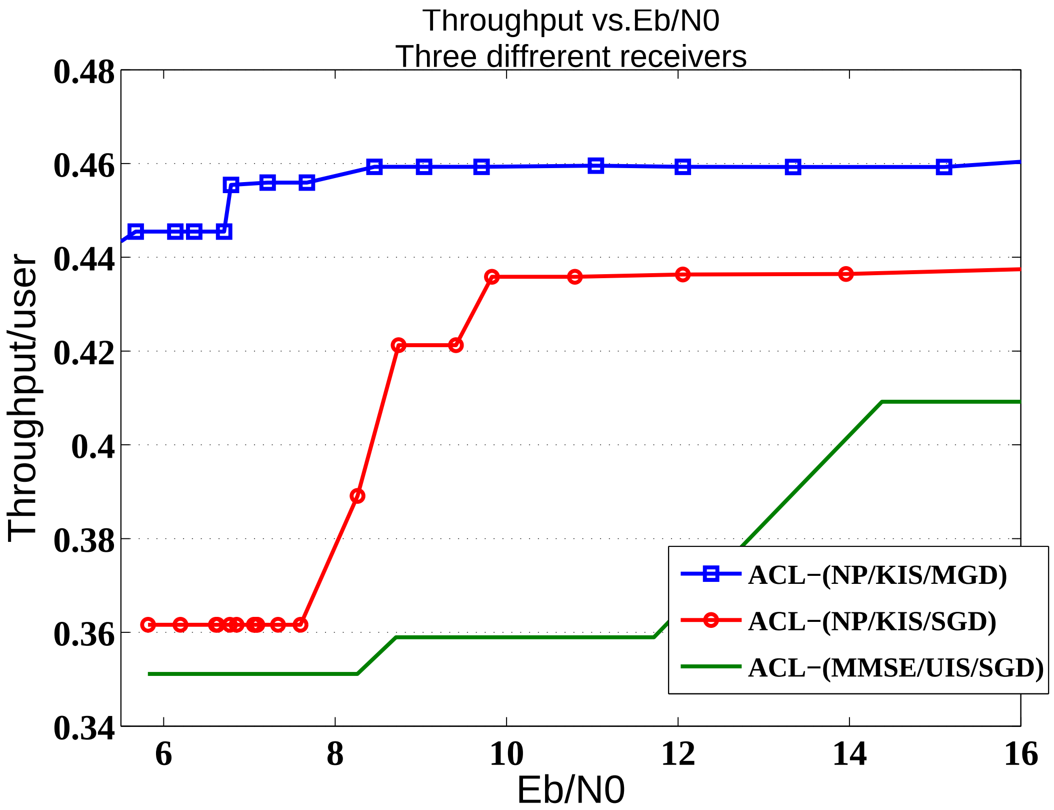
Numerical Results: Asymptotic Approximation Performance Loss



- **Even when the number of transmitters is very low, a finite network performs almost as well as the large interference network.**

(i) Arrival process: Poisson distribution with average rate $\lambda_k = 1$, (ii) CS varies according to a Markov chain with equal probability of keeping the state or changing to adjacent channel gain levels, (iii) Buffer states $= \{0, ..., 5\}$, Channel states $= \{0, ..., 2\}$, Power levels $= \{0, ..., 3\}$, Possible rates $= \{0, ..., 5\}$, $\bar{R} = 1$.

Numerical Results: Different Receivers



- **For ACL-(NP/KIS/MGD) the maximal throughput is limited by the maximum rate (i.e. we use a finite set of rates).**
- **For two other receivers, the maximal rate has interference limited behavior.**

(i) Arrival process: Poisson distribution with average rate $\lambda_k = 1$, (ii) CS varies according to a Markov chain with equal probability of keeping the state or changing to adjacent channel gain levels, (iii) Buffer states $= \{0, ..., 5\}$, Channel states $= \{0, ..., 2\}$, Power levels $= \{0, ..., 3\}$, Possible rates $= \{0, ..., 5\}$, $\bar{R} = 1$.

Summary, Remarks, and Observations

- We considered different receivers based on assumptions on: (I) the level of knowledge about interference, (II) Use of pre-decoding processing (e.g. detection), (III) single/multi group decoder.
- The asymptotic approach enables a sizable complexity reduction: the complexity does not scale with the number of users but with the number of transmitter groups.
- Policies obtained for dense networks are an excellent approximation also for networks with low communication flows: performance loss is very low.
- "Saturated queues" approach causes a relevant performance loss since the power is not efficiently allocated.

Outlines

Concluding Remarks

- **Resource allocation schemes for slow fading networks.**
- **Understanding the impact of different levels of CSI at transmitters on the design and optimality of resource allocations.**
- **Design distributed joint rate and power allocations in slow fading networks with partial CSIT in OFDM-based MAC.**
  - **Great complexity reduction in two steps: via duality theory and via game theory.**
  - **Excellent tradeoff between complexity and performance.**

Concluding Remarks

- **Cross-layer design of power and rate allocation, scheduling, and admission control in finite and dense interference networks.**
  - **Cross-layer approaches outperform significantly "saturated queues" approach.**
  - **Use of the throughput as objective function outperform significantly the use of approaches neglecting outage events.**
  - **Reduction of complexity via**
    - **reduction of stochastic games to linear programming.**
    - **asymptotic approximation of large networks via random matrix theory.**

Possible Future Extensions

- To investigate the effects of cooperation on the performance of the proposed distributed mechanisms (e.g., distributed pricing).
- To investigate the limiting point of the NE performance in our games of incomplete information as the number of players increases.
- To extend the problem into multi-hop ad hoc networks.

Thank you!