Adaptation, coordination and distributed resource allocation in interference-limited wireless networks

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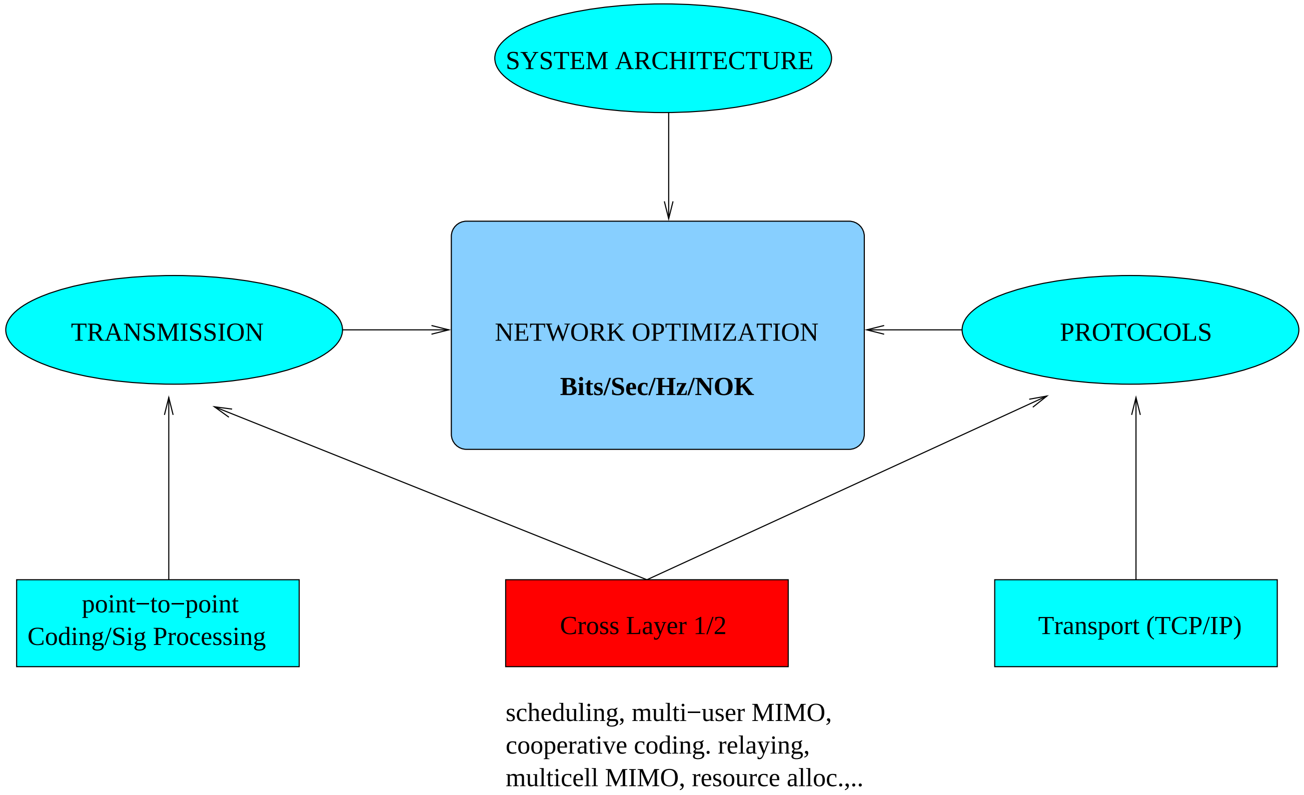
Thanks to my collaborators!

Wireless research a la Carte



Outline

- Cooperation vs. coordination
- Cellular vs. adhoc networks
- User vs. infrastructure cooperation
- Coding-based vs. resource allocation-based cooperation
- Some interesting cases
- Open problems

Cooperation vs. coordination

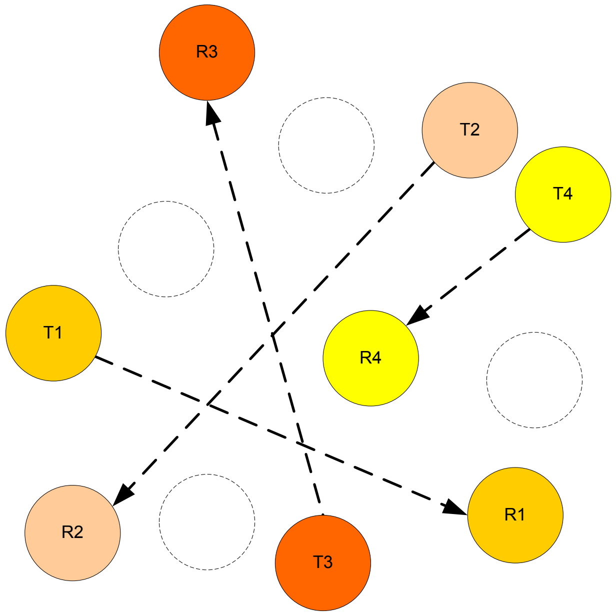
Two fundamental limitations:

- Fading limits the communication rate of any point to point link.
- Interference limits the reusability of spectral resource in space.

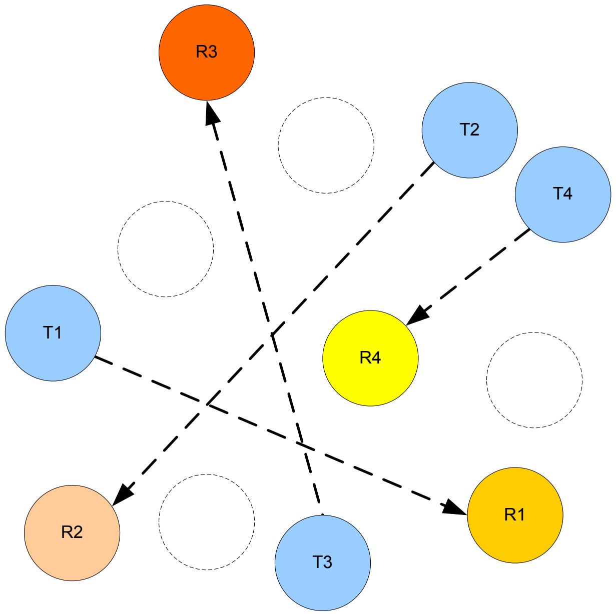
Cooperation schemes:

- Pooling Degrees of Freedom of many transceivers into a single basket.
- Optimizing the degrees of freedom to maximize rates, reliability and reuse.
- Several performance metrics. We choose Network's sum throughput.

Non-cooperating network



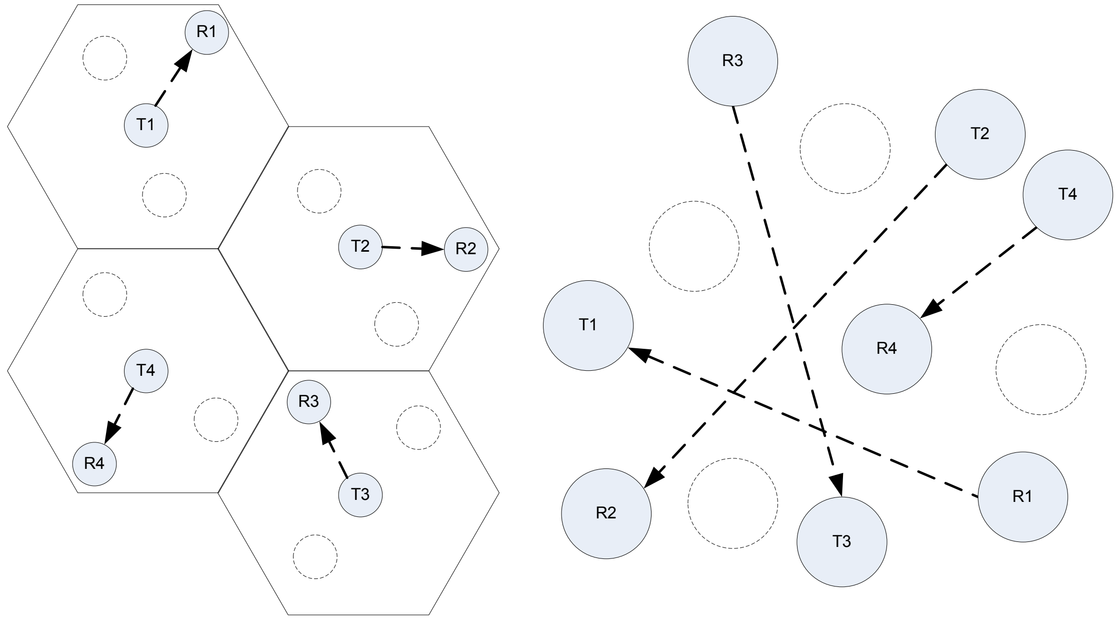
Cooperating network



Degrees of freedom for cooperation:

- Power
- Delay
- Bandwidth
- Antennas
- Users (scheduling)

Cellular vs. Adhoc

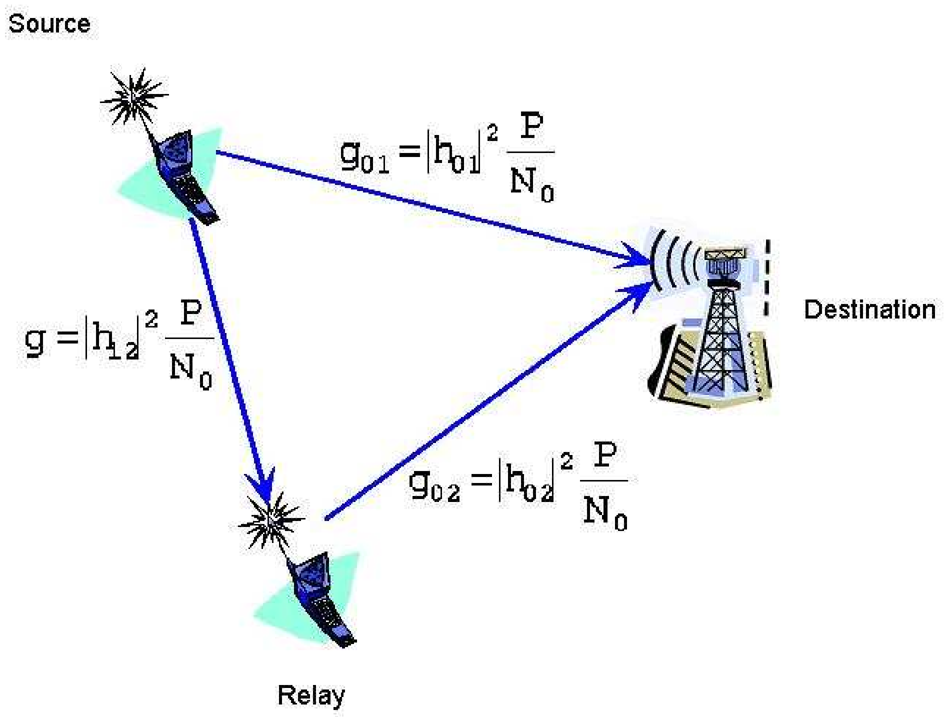


(a) (b)

- "cellular": Users connect to an infrastructure point, close-by.
- "Adhoc": Destinations are other abitrary located users.

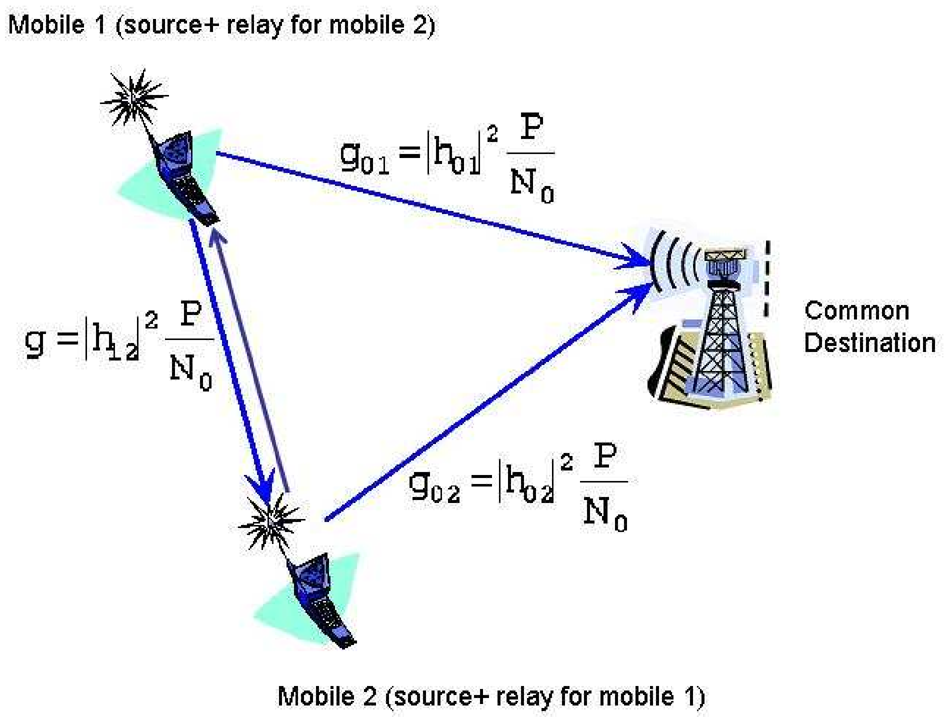
User-based cooperation (conventional)

- Conventional source-relay-destination framework emphasizes diversity gain for the source user.



Mutual cooperation

- Mutual cooperation balances benefit of relaying vs. overhead.
- Goal is to maximize Rate user1 + Rate user2.



A mutual cooperation protocol

Assumptions:

- Non-orthogonal Amplify-Forward protocol (NAF) [1]
- Each mobile divides its power across relay and own transmission tasks over time
- User 1 allocates α Watts for relaying user 2's data, keeps $1-\alpha$ for own transmission.
- User 2 allocates β Watts for relaying user 1's data, keeps $1-\beta$ for own transmission.

[1] [Azarian, El Gamal, Schniter] Trans IT 05.

Expression of sum rate (mobile 1 + mobile 2)

Lemma: For the Gaussian memoryless multiple-access channel, the sum-rate is such that $R1 + R2 \leq I_{\alpha,\beta}$ where [2]

$$I_{\alpha,\beta} = log_2 \left[1 + \gamma_{01} + (1-\alpha)\frac{K_1}{l_1(\beta)} + f(\beta\gamma_{02}, \gamma_{21}) \right] + log_2 \left[1 + \gamma_{02} + (1-\beta)\frac{K_2}{l_2(\alpha)} + f(\alpha\gamma_{01}, \gamma_{12}) \right]$$

where

$$K_1 = \left[\gamma_{01}^2 + \gamma_{01}\right]\left[\gamma_{21} + 1\right]$$
$$K_2 = \left[\gamma_{02}^2 + \gamma_{02}\right]\left[\gamma_{12} + 1\right]$$
$$l_1(\beta) = 1 + \gamma_{21} + \beta\gamma_{02}$$
$$l_2(\alpha) = 1 + \gamma_{12} + \alpha\gamma_{01}$$
$$f(x,y) = \frac{xy}{x+y+1}$$

[2] [Tourki, Gesbert, Deneire] ISIT'07

 EURECOM

Mutual cooperation is selfish!

Lemma: Optimal power allocation is given by either [2]

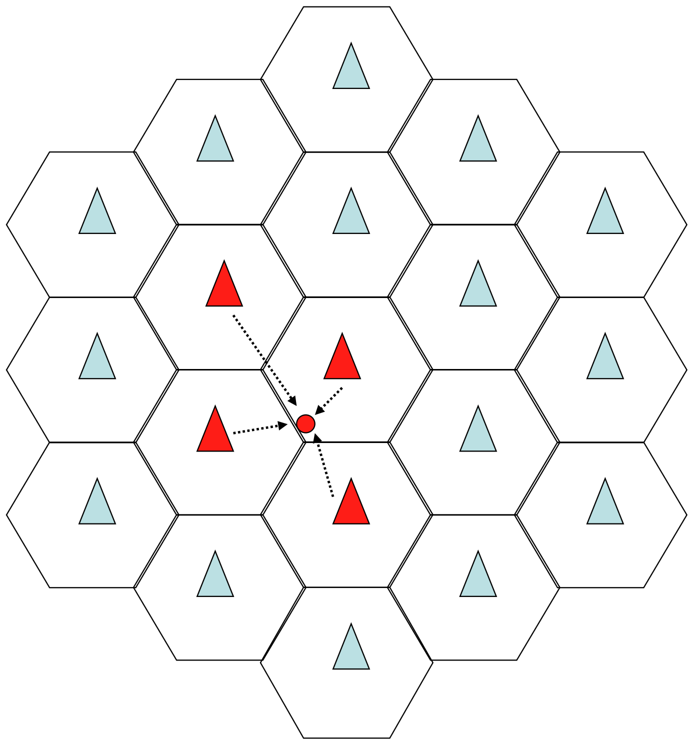
1. $\alpha = \alpha_* \neq 0$ and $\beta = 0$ if $\begin{cases} \gamma > \gamma_{02}^2 + \gamma_{02} \\ \gamma_{01} > \frac{(1+\gamma_{02})^2(1+\gamma)}{\gamma-(\gamma_{02}^2+\gamma_{02})} - 1 \end{cases}$
2. $\alpha = 0$ and $\beta = \beta_* \neq 0$ if $\begin{cases} \gamma > \gamma_{01}^2 + \gamma_{01} \\ \gamma_{02} > \frac{(1+\gamma_{01})^2(1+\gamma)}{\gamma-(\gamma_{01}^2+\gamma_{01})} - 1 \end{cases}$
3. $\alpha = 0$ and $\beta = 0$ if neither condition above is met.

At most one user cooperates with the other one:

($\Rightarrow$ opportunistically selfish behavior!)

[2] [Tourki, Gesbert, Deneire] ISIT'07

Infrastructure-based cooperation



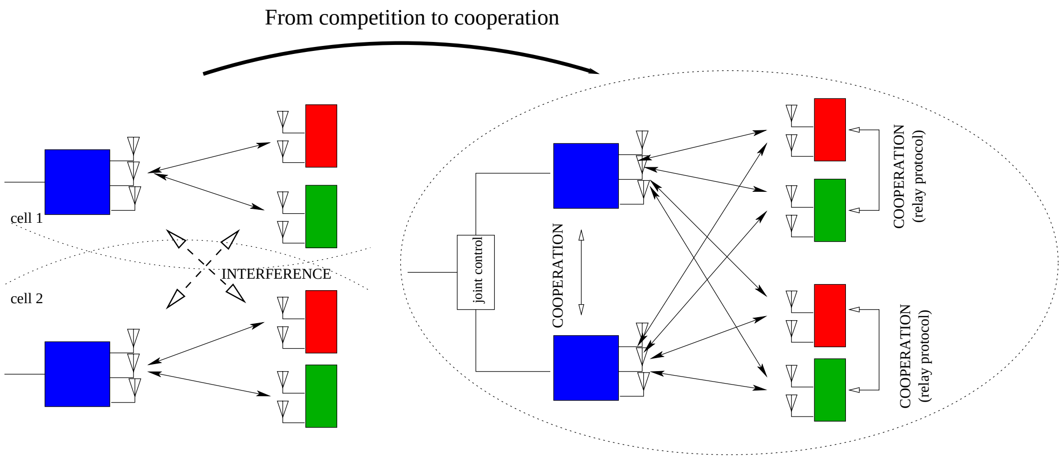
Levels of infrastructure cooperation

Several levels:

- Coding, signal processing level
  - Data routed to multiple access points
  - Optimum use of the available radio links
  - Centralized control required
- Resource allocation level
  - Data routed to a single access point
  - Interference is a problem but reduced coordinated power control and scheduling
  - Scalable with network size
  - Distributed solutions?

coding, signal processing-based cooperation

Interference ⇒ Energy ⇒ Additional data pipe ⇒ good for you!

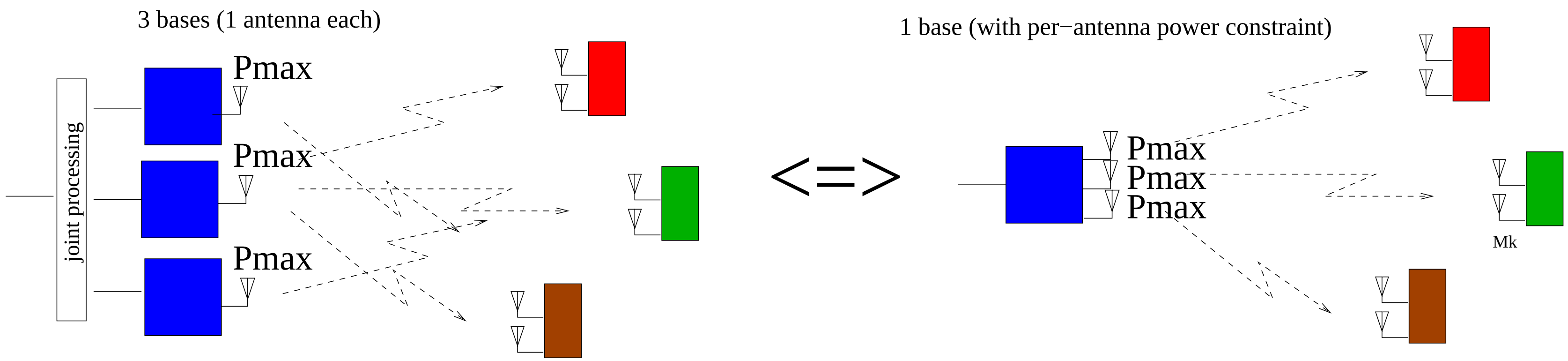


Capacity of Multicell MIMO can be reached as regular multi-user MIMO capacity with additional power constraints [3][4]

[3] [Shamai, Zaidel] VTC'01

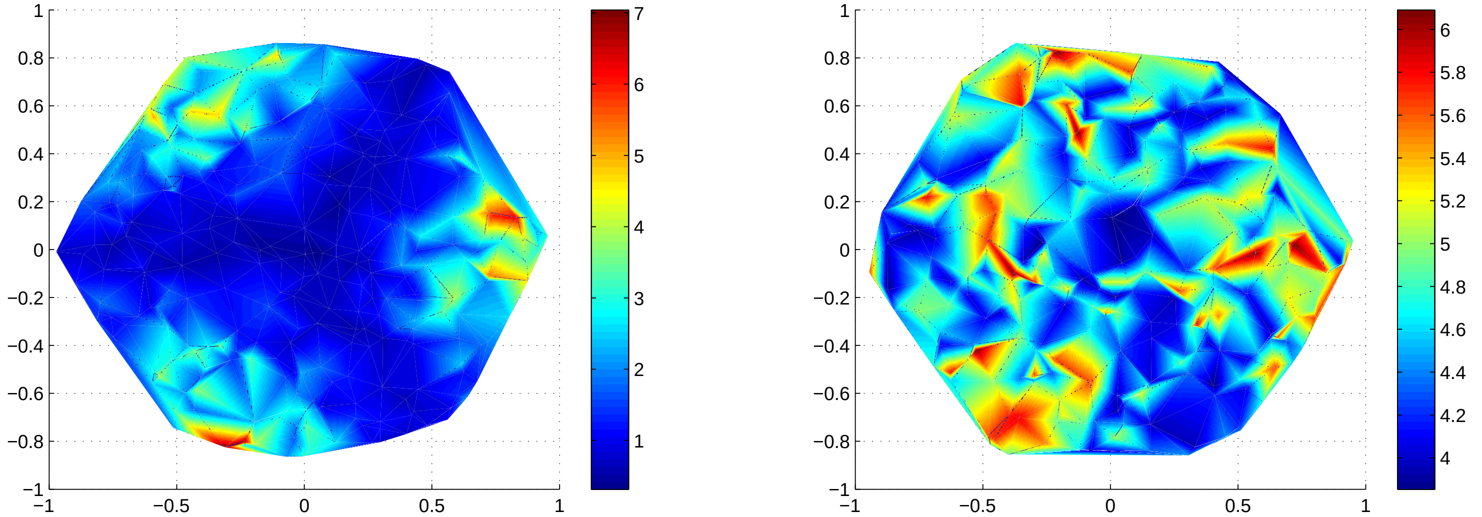
[4] [Karakayali, Foschini, Valenzuela, Yates] ICC'06

MIMO vs. Multicell MIMO



Three cell MIMO network

Rate performance without (left) and with MIMO cooperation (three sectors in hexagon)



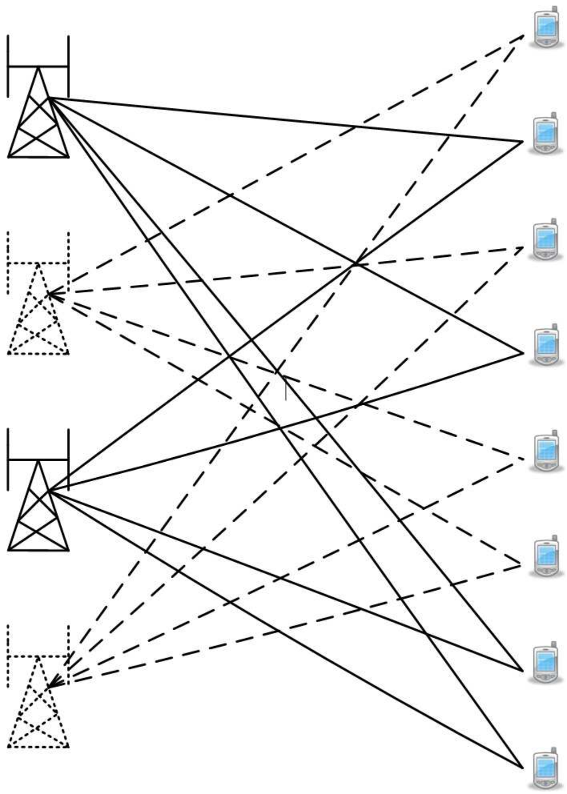
(a) Without coop

(b) With coop

Multi-cell MIMO in practice

- Gives significant advantage for edge-of-cell users if hard fairness is enforced.
- Easy to implement for small subnets (2 cells)
- Many cells cooperating may be difficult due to inter-cell CSI overhead
- Routing in backhaul must be optimized
- Dynamic clustering can be a solution

Multi-cell multiplexing with Dynamic clustering [5]



[5] [Papadogiannis, Gesbert] ICC’08 Submitted

Resource allocation-based cooperation

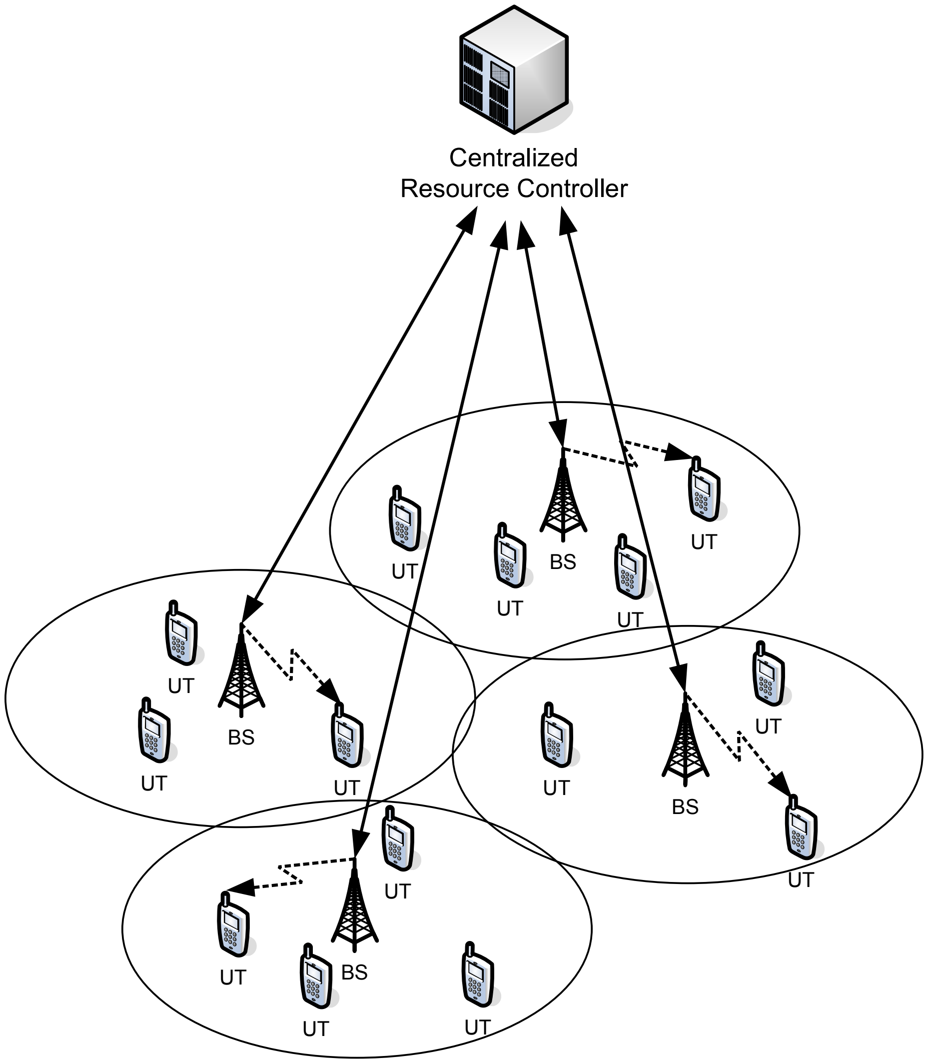
Motivations:

- Multicell-MIMO is not scalable.
- Distributed MIMO signal processing hard.
- Broadcast routing of data not always desirable.
- Can we achieve cooperation gains without it?

Remaining degrees of freedom:

- Delay (equivalently user scheduling)
- Power
- bandwidth

Centralized resource allocation



Optimal scheduling and power control

Searching over all scheduling vectors $\boldsymbol{U}$ and power vectors $\boldsymbol{P}$:

$$(\boldsymbol{U}^*, \boldsymbol{P}^*) = \arg\max_{\substack{\boldsymbol{U}\in\Upsilon \\ \boldsymbol{P}\in\Omega}} \mathcal{C}(\boldsymbol{U}, \boldsymbol{P}), \tag{1}$$

where:

$$\mathcal{C}(\boldsymbol{U}, \boldsymbol{P}) \triangleq \frac{1}{N} \sum_{n=1}^{N} \log\Big(1 + \Gamma([\boldsymbol{U}]_n, \boldsymbol{P})\Big). \tag{2}$$

and the SINR in cell n is:

$$\Gamma([\boldsymbol{U}]_n, \boldsymbol{P}) = \frac{G_{u_n,n} P_{u_n}}{\sigma^2 + \sum_{i\neq n}^{N} G_{u_n,i} P_{u_i}}, \tag{3}$$

A surprising result for two cells

Theorem:

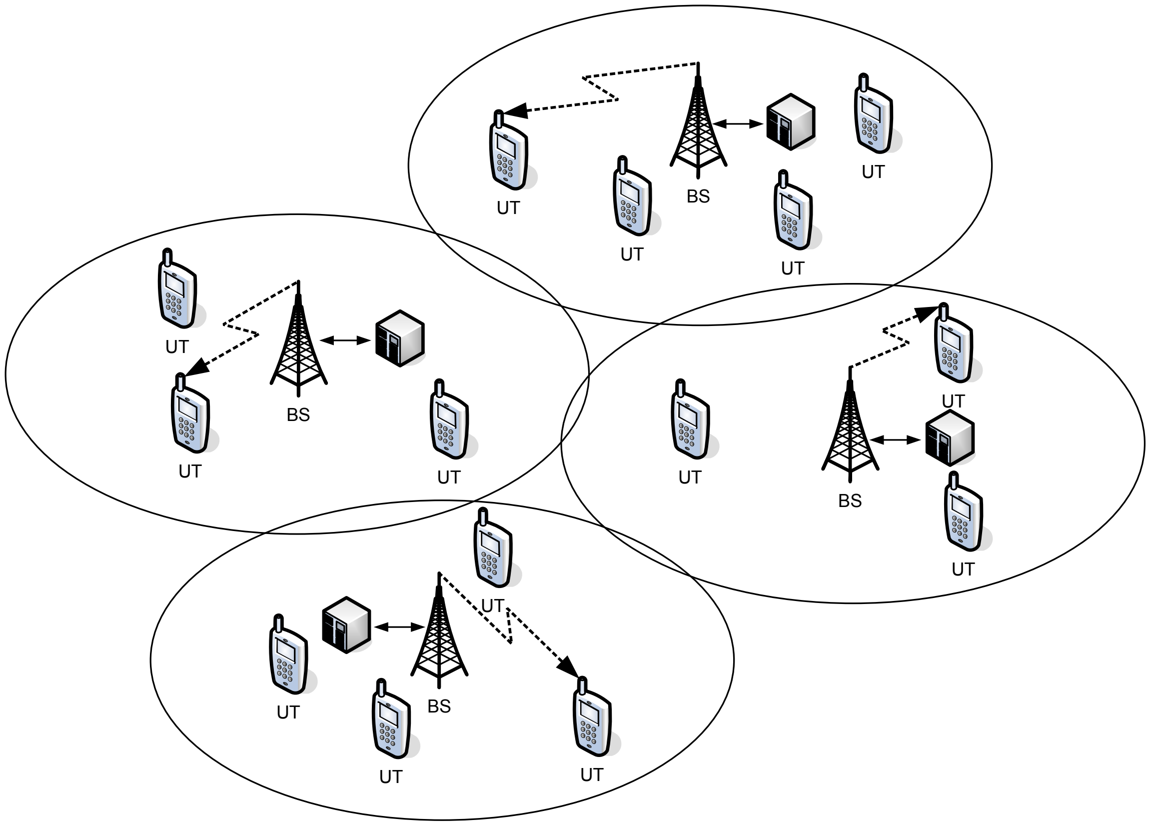
For two cells, the optimum power allocation is ON-OFF:

$$\arg \max_{(P_1,P_2)\in\Delta\Omega^2} \mathcal{C}(\boldsymbol{U},(P_1,P_2)) = \arg \max_{(P_1,P_2)\in\Omega} \mathcal{C}(\boldsymbol{U},(P_1,P_2)) \tag{4}$$

where $\Delta\Omega^2 = \{(P_{max},0),(0,P_{max}),(P_{max},P_{max})\}$

[6] [Gjendemsjoe, Gesbert, Oien , Kiani] IEEE Trans. Wireless Comm. to appear.

But we want...distributed resource allocation



Paths toward distributed allocation [7]

- Game theoretic approaches
- Stastical optimization approaches
- Optimization under ON-OFF power control model
- Optimization in the large number of user case

[7] [Gesbert, Kiani, Gjendemsjoe, Oien] Proceedings of the IEEE, 2007.

Game theoretic approaches

The non-cooperative power control game [8][9] writes

$$\max_{0 \le p_n \le P_n^{\max}} \; f_n(p_n, \mathbf{p_{-n}}) \; \forall \; n.$$

or with pricing

$$\max_{0 \le p_n \le P_n^{\max}} \; \{f_n(p_n, \mathbf{p_{-n}}) - c_n(p_n)\} \; \forall \; n.$$

where f_n is selfish utility of user n. Nash equilibrium may not maximize network utility.

Cooperative games lead to Nash bargaining equilibrium, socially more optimal, but non-distributed.

[8] [Meshkati, Poor, Schwartz] IEEE SP Magazine 2007

[9] [Goodman, Mandayam] IEEE Personal Comm. Mag 2000

Optimization under ON-OFF power control

Let $\tilde{N}$ is the number of active cells, assumed large.

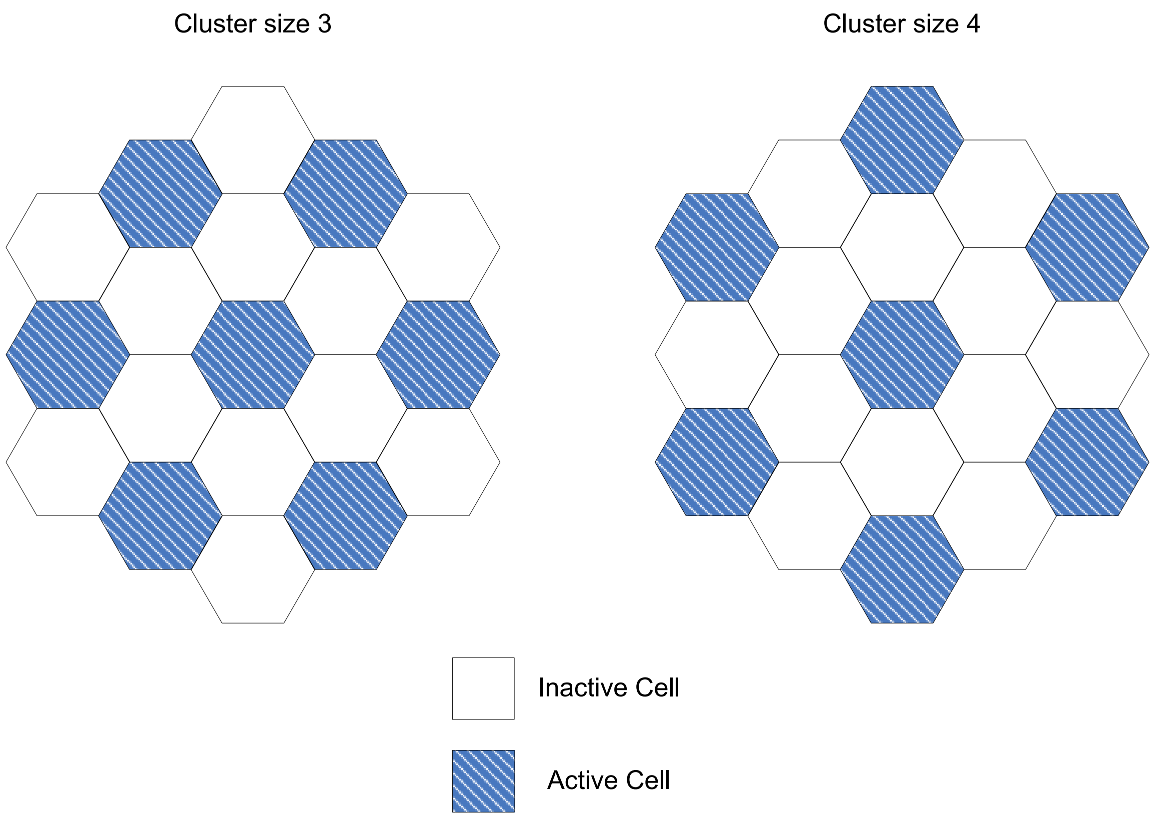
Cell m weighs its capapcity contribution to the system against the interference it generates:

Cell m is activated if (Capacity (with cell m) > Capacity (without cell m)), that is if

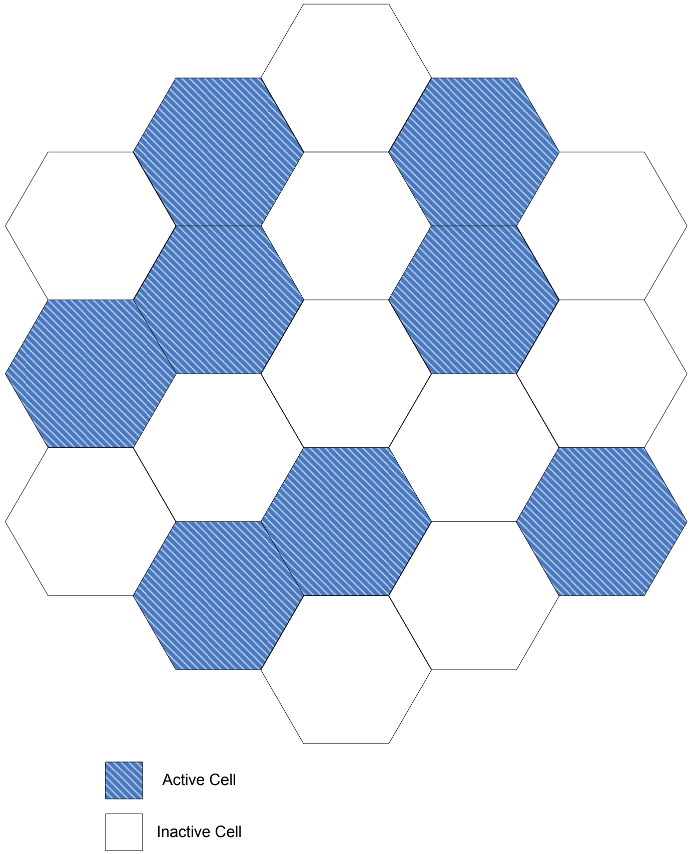
$$\Gamma([\boldsymbol{U}]_n, \boldsymbol{P}) \geq \frac{\prod\limits_{\substack{n \in \mathcal{N} \\ n \neq m}} \sum\limits_{\substack{i \neq n \\ i \in \mathcal{N}}} P_i}{\prod\limits_{\substack{n \in \mathcal{N} \\ n \neq m}} \sum\limits_{\substack{i \neq n \neq m \\ i \in \mathcal{N}}} P_i} = \left(\frac{\tilde{N} - 1}{\tilde{N} - 2} \right)^{(\tilde{N}-1)} \approx e$$

Leads to opportunistic reuse patterns.

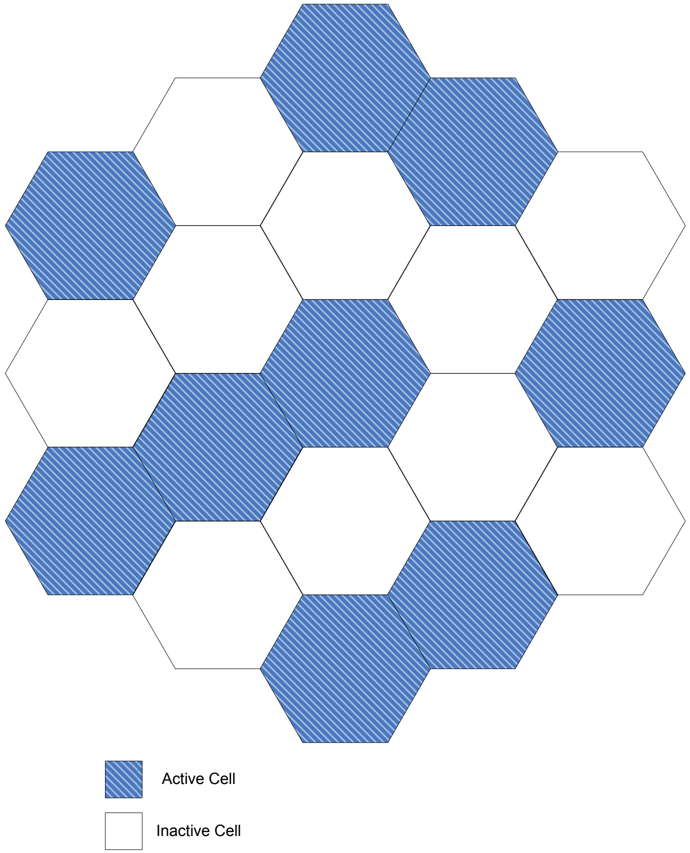
Static reuse patterns



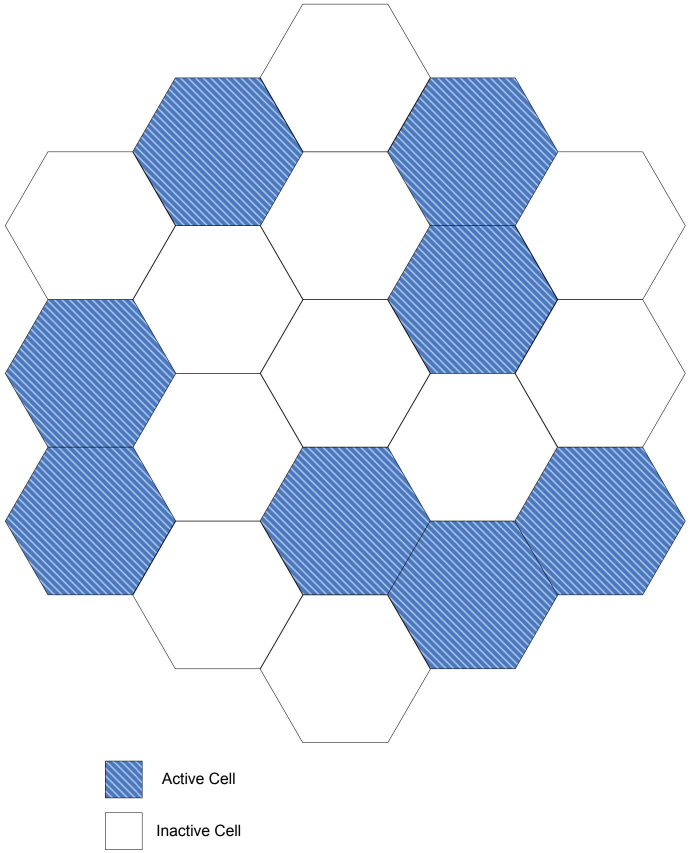
Opportunistic reuse pattern



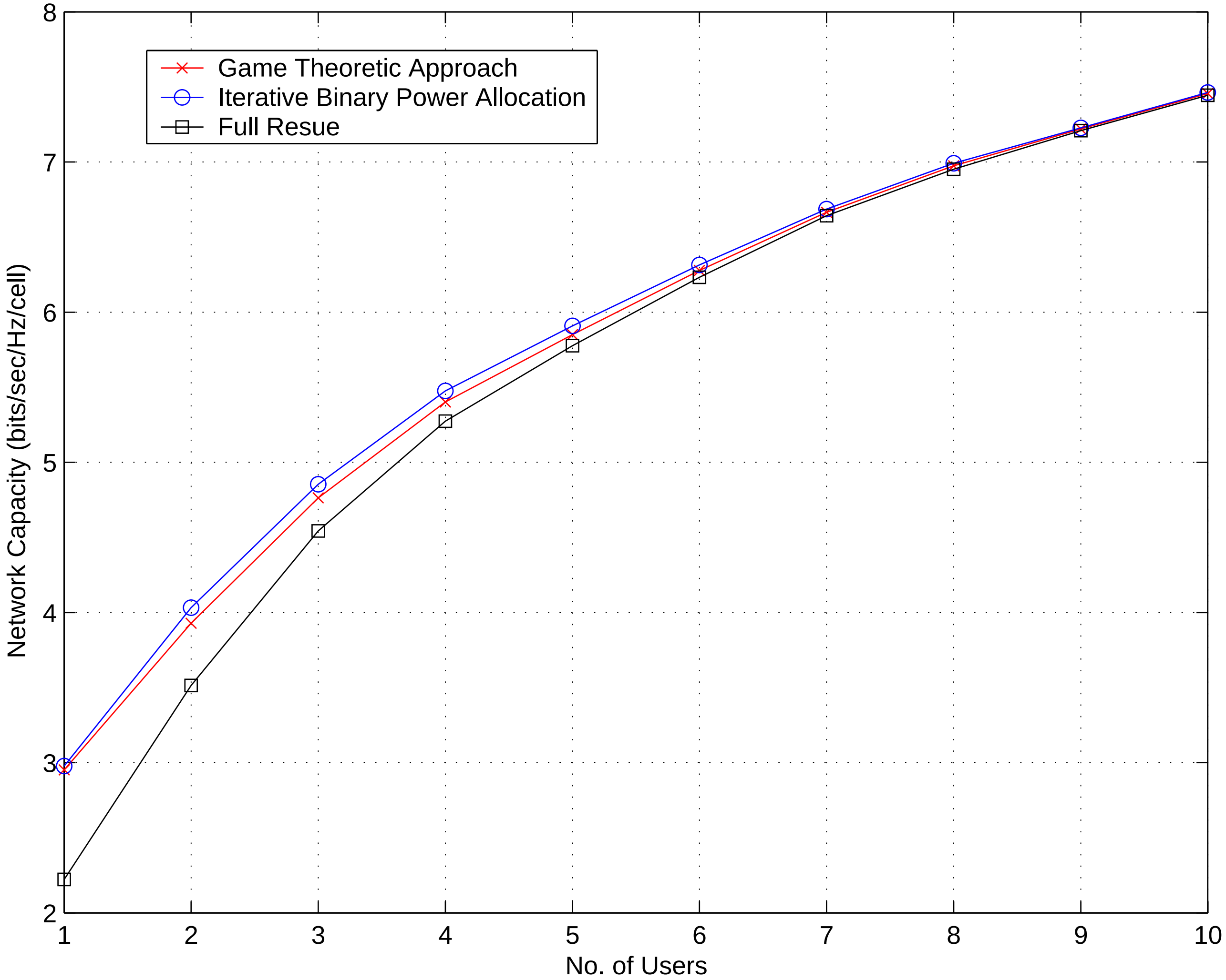
Opportunistic reuse pattern



Opportunistic reuse pattern



Capacity performance vs. number of users



The large number of users case

- We let number of users per cell grow asymptotically
- System capacity will grow with number of users

  $\Rightarrow$ (multi-user multi-cell diversity!)
- What is the loss due to interference ?
- What can we achieve with a distributed scheme (power control + scheduling)?

[Gesbert, Kountouris] IEEE Trans. IT 2007, submitted

A bounding approach

We study two bounds on capacity:

- Upper bound obtained with no interference
- Lower bound obtained with full powered interference

In three network scenarios:

1. All users have same average received power (located on circle around the base)
2. Users uniformly located in the cell
3. Users uniformly located but cannot get too close to the base

Upper bound on capacity: No interference

$$\mathcal{C}(\boldsymbol{U}^*, \boldsymbol{P}^*) \leq \mathcal{C}^{ub} = \frac{1}{N} \sum_{n=1}^{N} \log\left(1 + \Gamma_n^{ub}\right). \tag{5}$$

where the upper bound on SINR is given by:

$$\Gamma_n^{ub} = \max_{u_n=1..U} \{G_{u_n,n}\} P_{max}/\sigma^2 \tag{6}$$

The corresponding scheduler is the max SNR scheduler: Fully distributed

Lower bound on capacity: Full interference

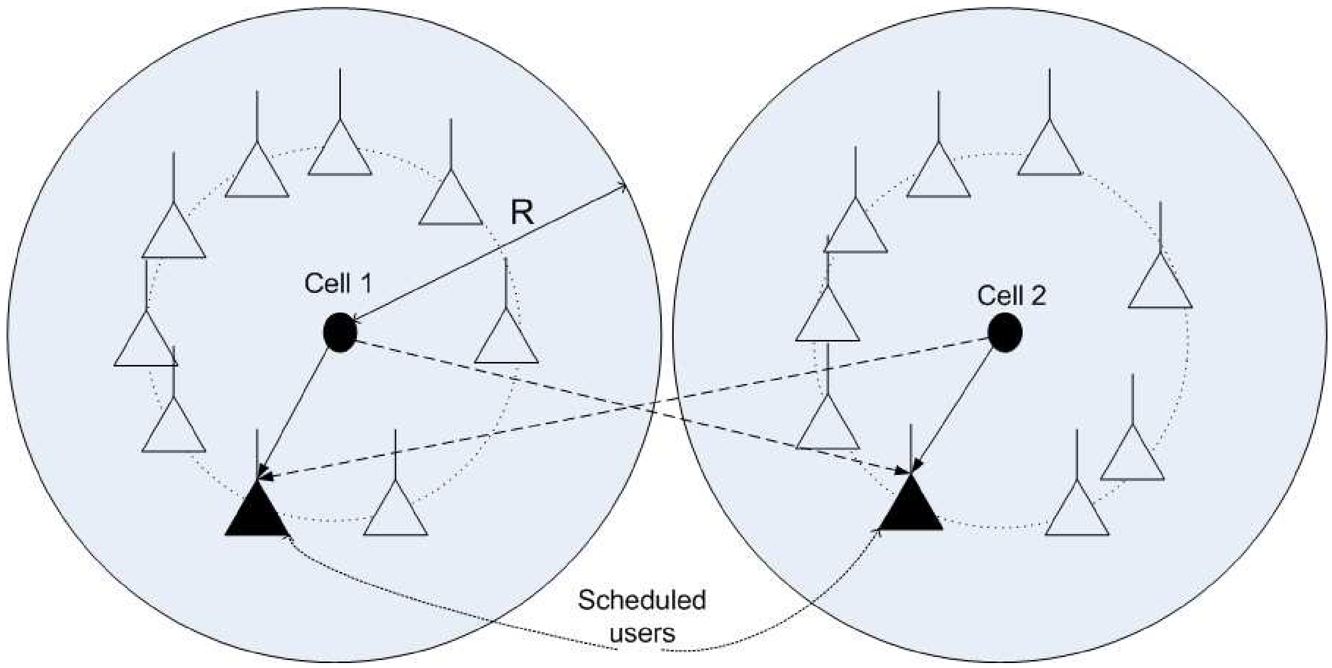
$$\mathcal{C}(\boldsymbol{U}^*, \boldsymbol{P}^*) \geq \mathcal{C}^{lb} = \mathcal{C}(\boldsymbol{U}^*_{FP}, \mathbf{P}_{max}) \tag{7}$$

$\boldsymbol{U}^*_{FP}$ is the optimal scheduling vector assuming full interference, defined by

$$[\boldsymbol{U}^*_{FP}]_n = \arg\max_{\boldsymbol{U}\in\Upsilon} \left(\Gamma^{lb}_n = \frac{\{G_{u_n,n}\} P_{max}}{\sigma^2 + \sum_{i \neq n}^{N} G_{u_n,i} P_{max}} \right) \tag{8}$$

The corresponding scheduler is the max SINR scheduler: Also fully distributed

Capacity scaling for symmetric network



Capacity scaling with many users ($U \to \infty$)

In the interference-free case (using extreme value theory):

Lemma: For fixed N and U asymptotically large, the upper bound on the SINR in cell n scales like

$$\Gamma_n^{ub} \approx \frac{P_{max}\gamma_n}{\sigma^2} \log U \tag{9}$$

Theorem: For fixed N and U asymptotically large, the average of the upper bound on the network capacity scales like

$$E(\mathcal{C}^{ub}) \approx \log \log U \tag{10}$$

Capacity scaling with many users ($U \to \infty$)

In the full powered interference case (using extreme value theory):

lemma: For fixed N and U asymptotically large, the lower bound on the SINR in cell n scales like

$$\Gamma_n^{lb} \approx \frac{P_{max}\gamma_n}{\sigma^2} \log U \tag{11}$$

theorem Then for fixed N and U asymptotically large, the average of the lower bound on the network capacity scales like

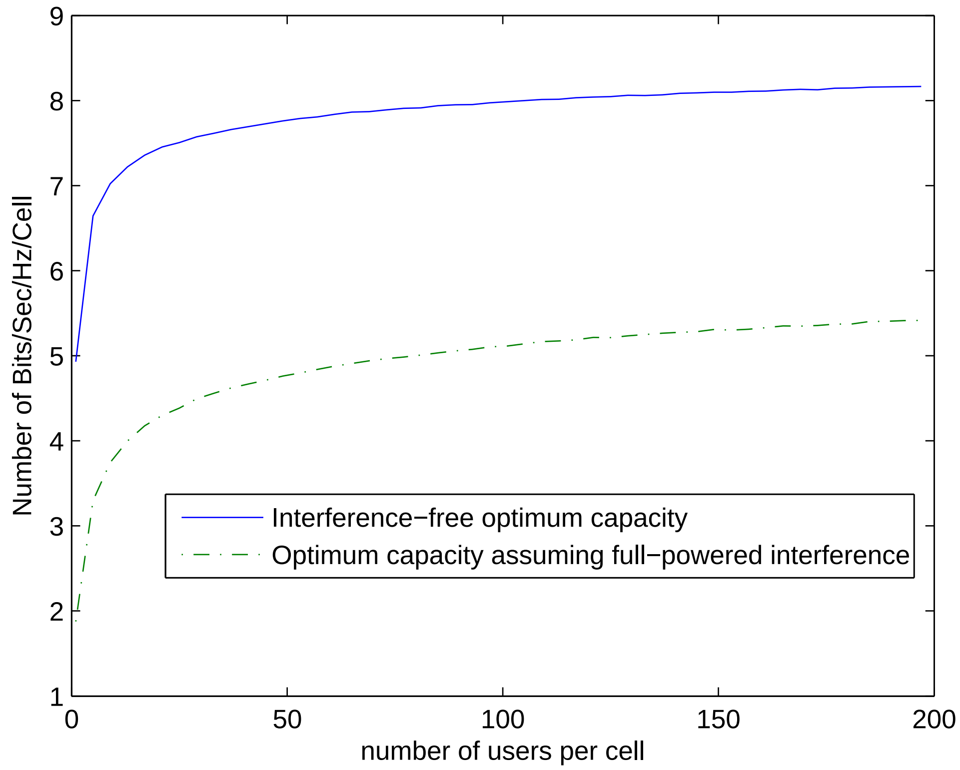
$$E(\mathcal{C}^{lb}) \approx \log \log U \tag{12}$$

System with and without interference have same growth rates!

Interpretations

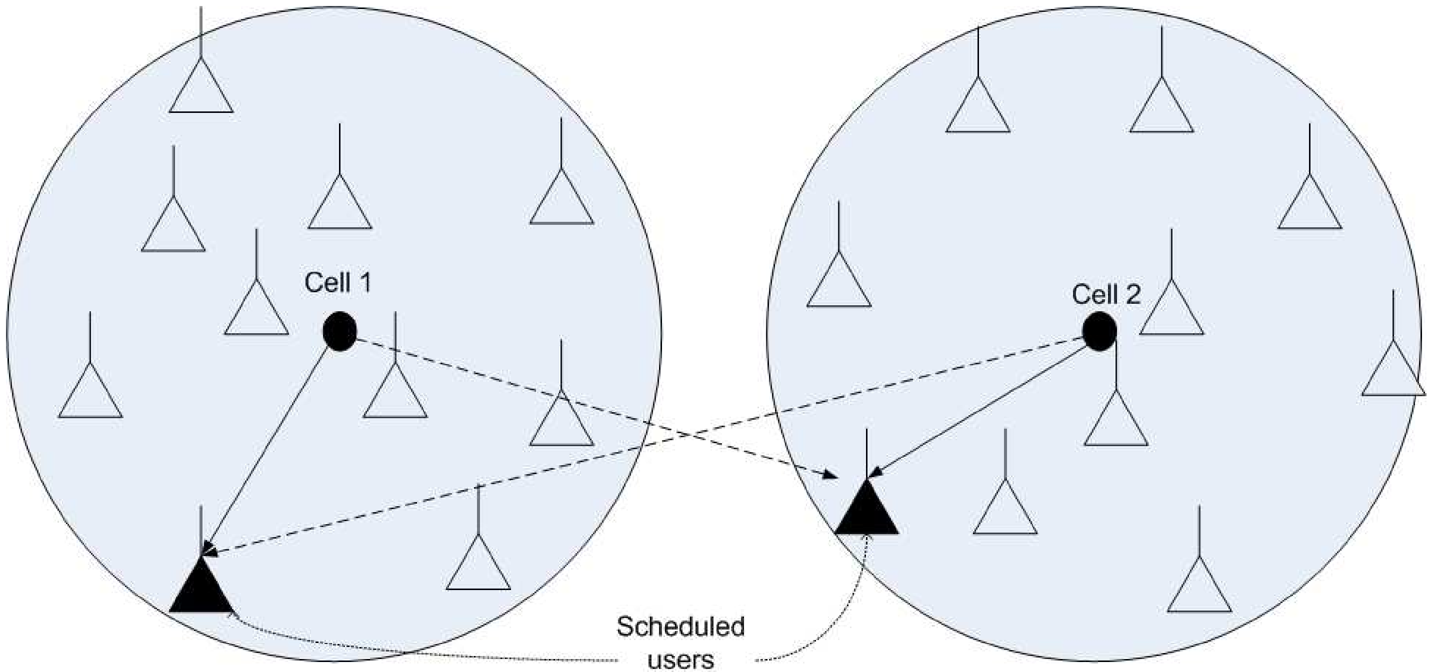
- Interference creates vanishing loss for large number of users
- Physically, the max-rate resource allocator looks for users which are
  - shielded from interference and
  - with large SNR
- When number of users is large, interference becomes small compared with noise.

Capacity scaling for symmetric network



Scaling of upper and lower bounds of capacity, versus U for a symmetric network ($N = 4$)

Capacity scaling for non-symmetric network



Important: Path loss fading has heavy tail behavior while Rayleigh fading has not

Capacity scaling for non-symmetric network

From extreme value theory of heavy-tailed random variables:

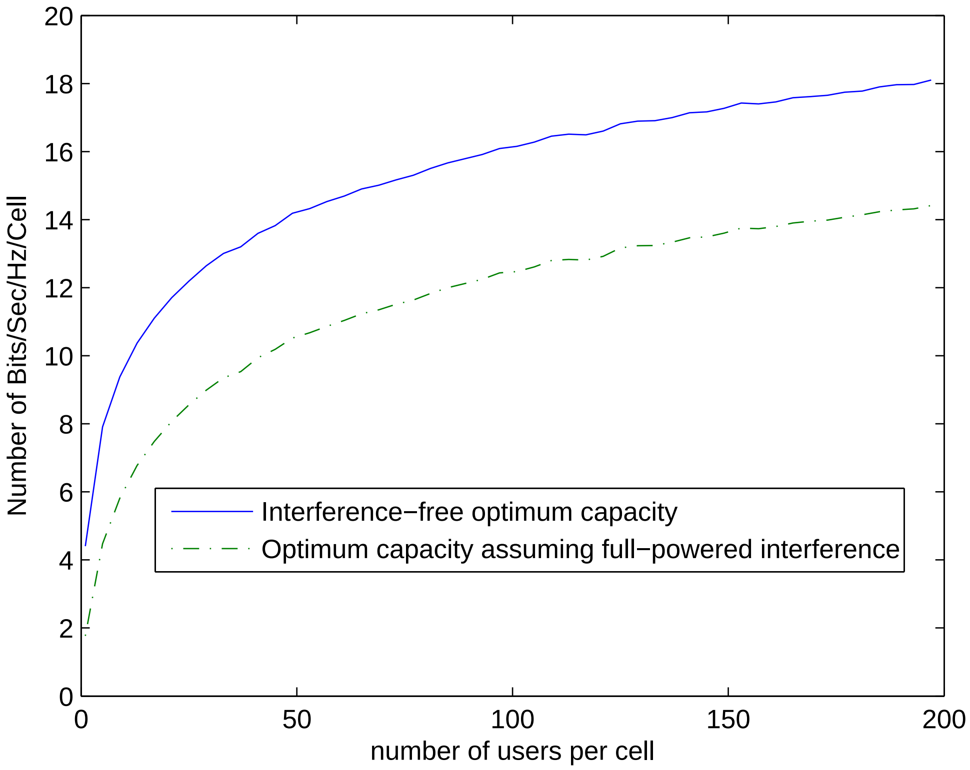
Theorem: The upper bound on capacity will behave like:

$$E(\mathcal{C}^{ub}) \approx \frac{\epsilon}{2} \log U \quad \text{for large } U \tag{13}$$

Theorem: The lower bound on capacity will behave like:

$$E(\mathcal{C}^{lb}) \approx \frac{\epsilon}{2} \log U \quad \text{for large } U \tag{14}$$

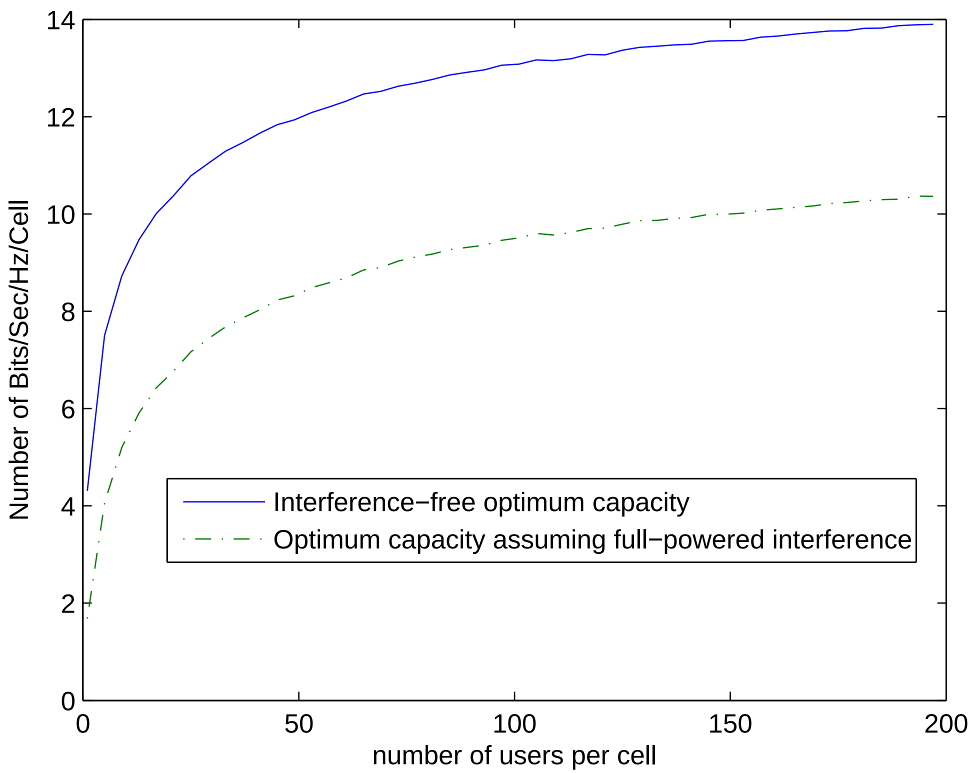
Capacity scaling for non-symmetric network



Scaling of upper and lower bounds of capacity, versus U for a non-symmetric network ($N = 4$)

Capacity scaling for hybrid network

Users excluded from disk with radius 5 percent of cell radius.



Scaling of upper and lower bounds of capacity, versus U for a hyrbid network ($N = 4$)

Conclusions

- Large number of users reveals simple structure of the resource allocation problem:
  - Fully ditributed solution possible
  - Price paid due to interference is small
- QoS-oriented scheduling will give different results

Open problems

Cooperation creates gains and challenges:

- May affect routing
- Easier with infrastructure based cooperation (than user-based)
- In theory, each user receives tiny bits of information through everybody else.
- In practice, optimization must be distributed to keep information exchange local
- More issues: Synchronization, QoS guarantee issues
- Promising avenue: A two-scale optimization within a single network
  - Small scale: coding, signal processing based cooperation (multicell MIMO)
  - Large scale: resource allocation-based