







Optimal Resource Allocation in Distributed Heterogeneous 5G Wireless Networks

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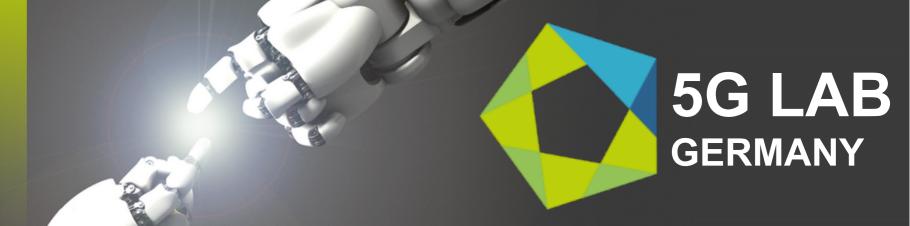


joint work with

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- Stefano Buzzi (Uni Cassino, Italy)
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- Merouane Debbah (CentraleSupelec, France)
- Emil Björnson (Linköping Uni, Sweden)
- Björn Ottersten (KTH & Uni Luxembourg)



Holistic View on 5G





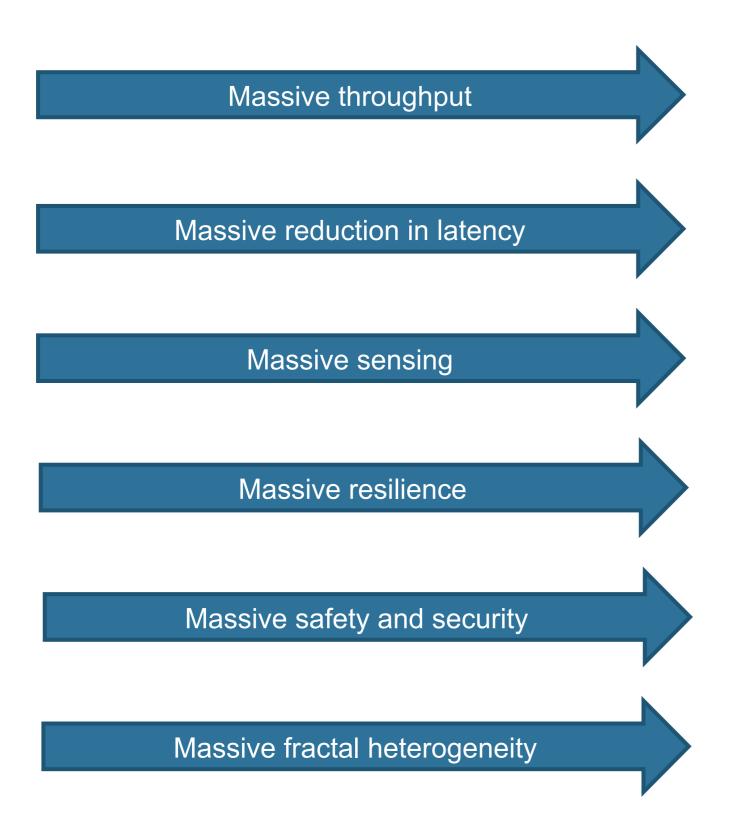
Data Rate

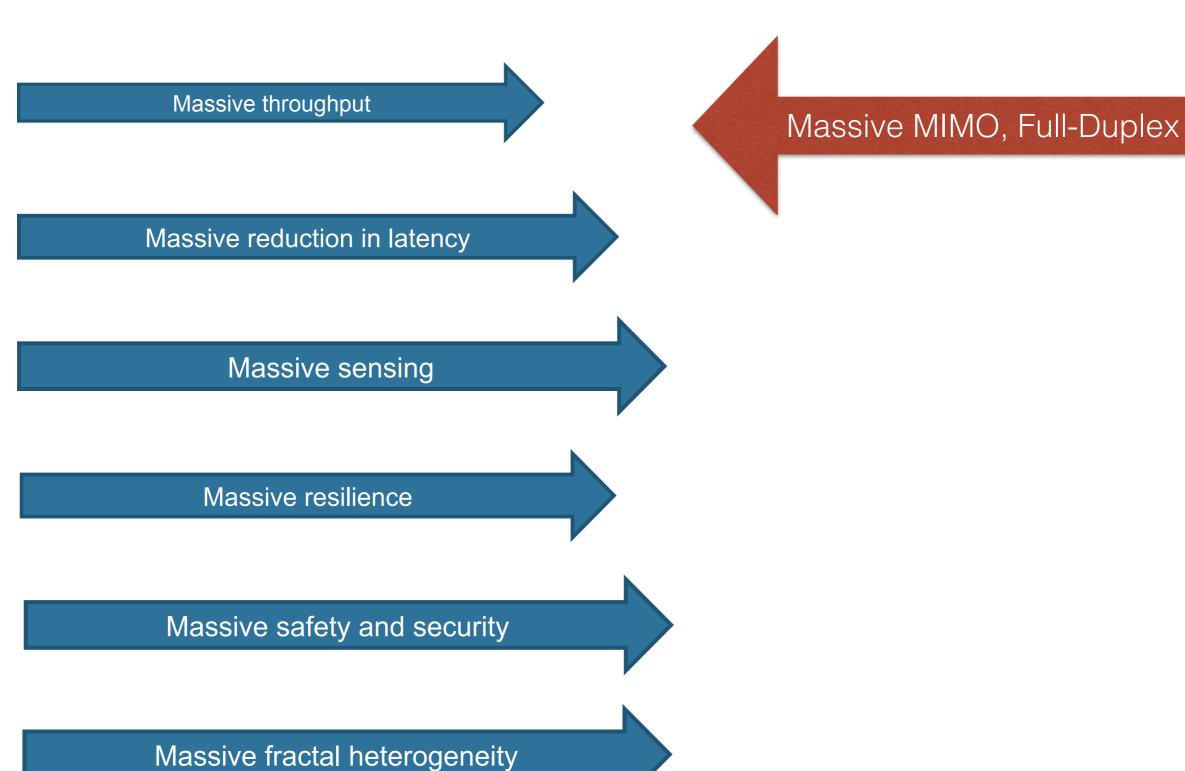
Latency

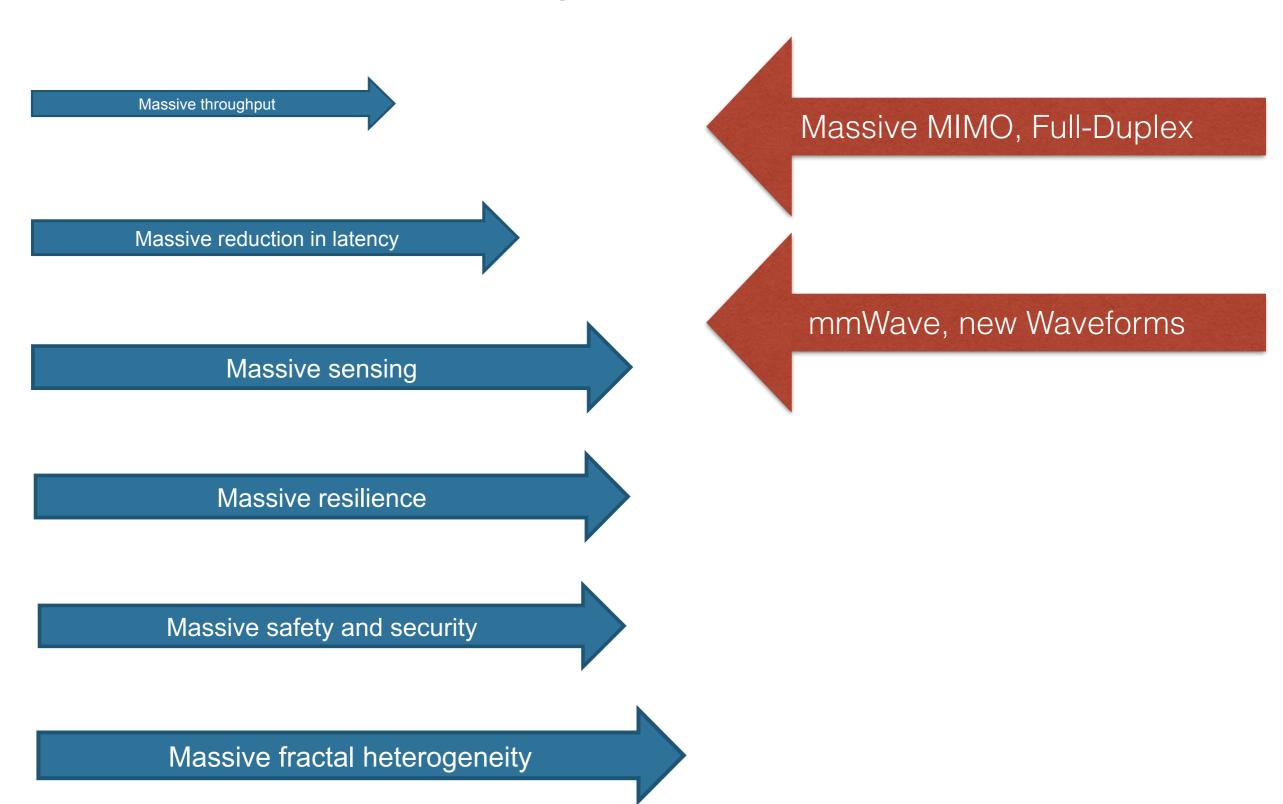
Security

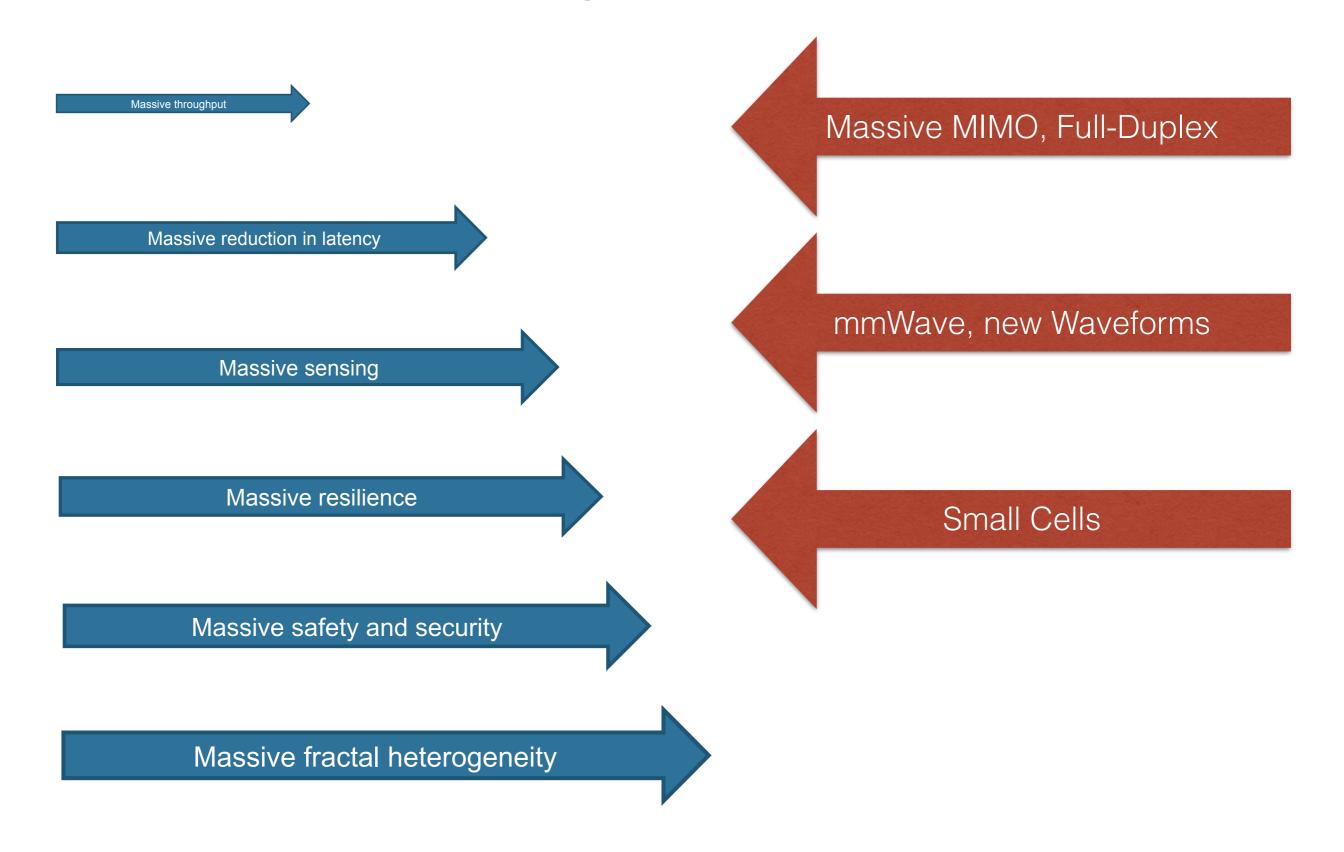
Reliability

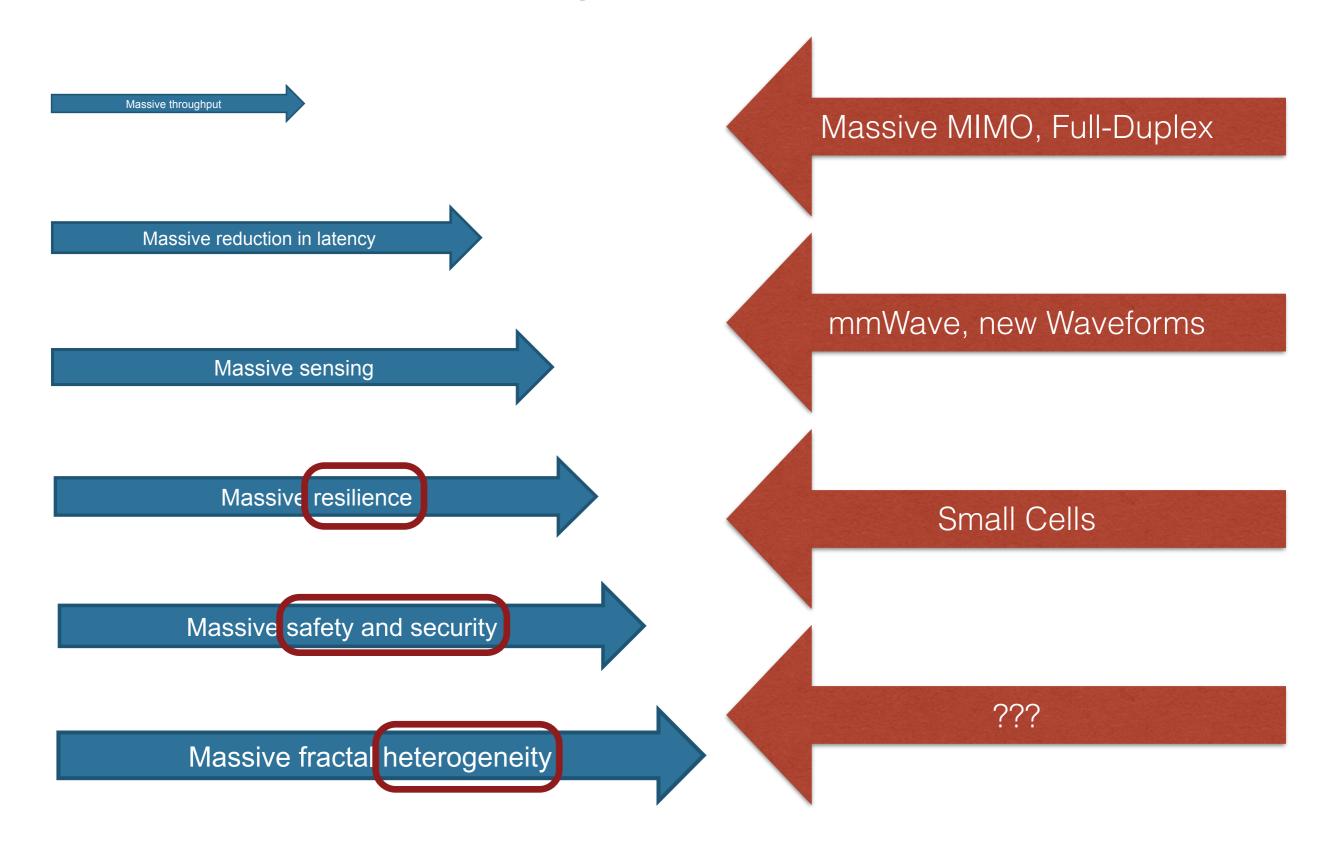
Heterogeneity





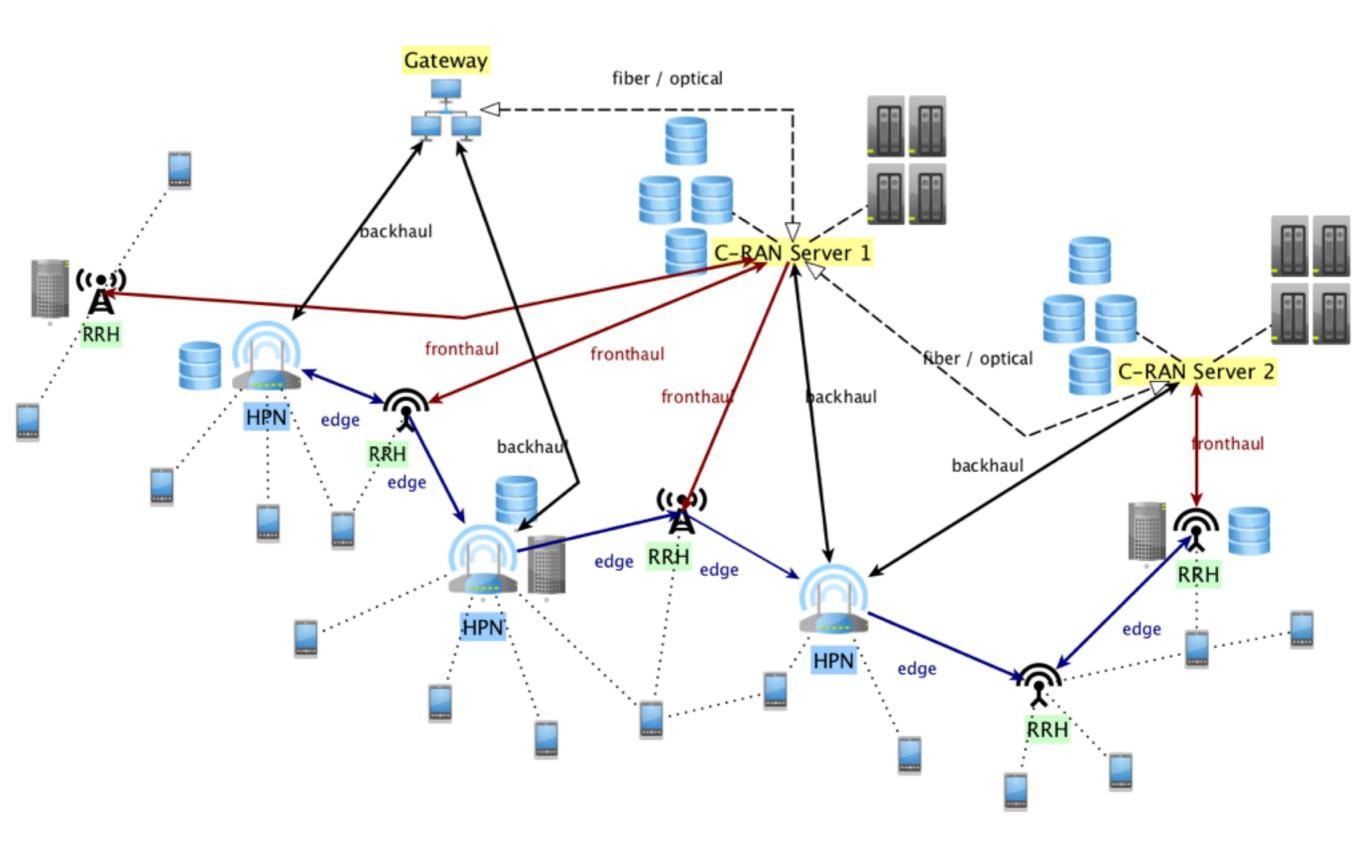






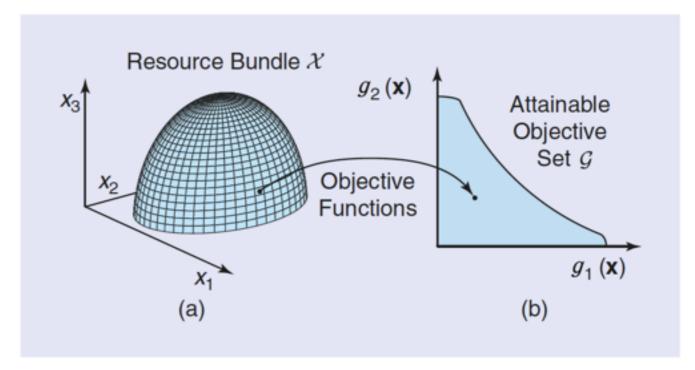
Outline

- Introduction
 - Heterogeneity (networks, users, services, ...)
 - Multi-Objective Optimization
- Framework for Energy-Efficient Resource Allocation
 - Centralized and Distributed Power Control
- Conclusions



Heterogeneous Services

- Conflicting performance metrics/requirements:
 - Data rate / throughput
 - Delay / latency
 - Energy efficiency
 - Security

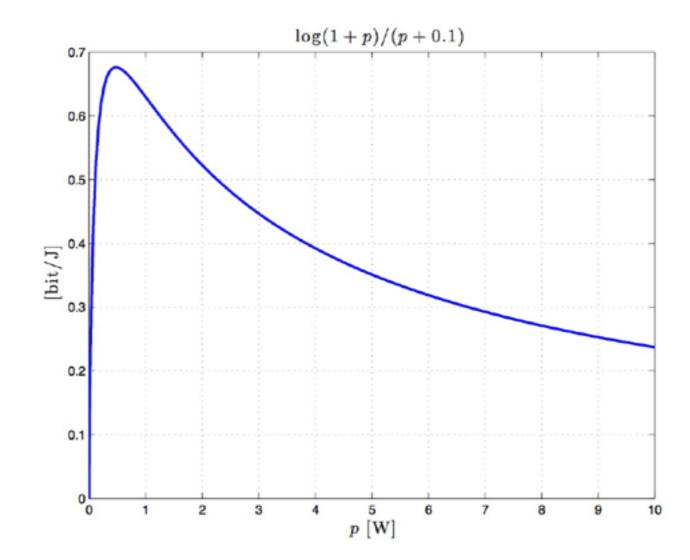


- Multi-Objective Programming (MOP) problem
- E. Björnson, E. Jorswieck, M. Debbah, B. Ottersten, "Multi-Objective Signal Processing Optimization: The Way to Balance Conflicting Metrics in 5G Systems", IEEE Signal Processing Magazine, vol. 31, no. 6, pp. 14-23, Nov. 2014.

Energy-efficiency of a link

In line with the physical meaning of efficiency, the **energy efficiency is defined** as the system benefit-cost ratio in terms of amount of data reliably transmitted over the energy that is required to do so.

$$EE = \frac{f(\gamma(p))}{\alpha p + P_c}$$



Energy-efficiency of a network

Global Energy-efficiency

$$GEE = \frac{\sum_{k=1}^{K} f(\gamma_k(\{p_k\}_{k=1}^{K}))}{\sum_{k=1}^{K} \alpha_k p_k + P_{c,k}}$$

Weighted arithmetic mean

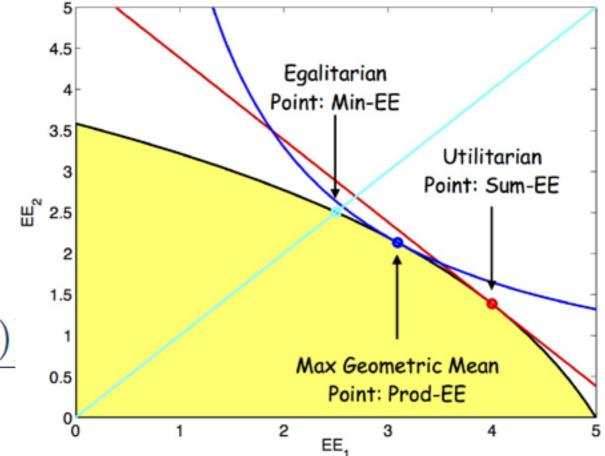
Sum-EE =
$$\sum_{k=1}^{K} w_k \frac{f(\gamma_k (\{p_k\}_{k=1}^K))}{\alpha_k p_k + P_{c,k}}$$

Weighted geometric mean

$$\mathsf{Prod}\text{-}\mathsf{EE} = \prod_{k=1}^K \left(\frac{f(\gamma_k(\{p_k\}_{k=1}^K))}{\alpha_k p_k + P_{c,k}} \right)^{w_k}$$

Weighted minimum EE

$$\mathsf{Min}\text{-}\mathsf{EE} = \min_{k} \left(w_k \frac{f(\gamma_k(\{p_k\}_{k=1}^K))}{\alpha_k p_k + P_{c,k}} \right)$$



Observation: always ratios

Fractional Programming

Single ratio: concave fractional problems

CFP

```
f(x) \ge 0, g(x) > 0, differentiable functions. f, concave, g, h_k convex for all k = 1, \dots, K.
```

$$\begin{cases} \max_{\boldsymbol{x}} \frac{f(\boldsymbol{x})}{g(\boldsymbol{x})} \\ \text{s.t. } h_k(\boldsymbol{x}) \leq 0 \text{ , } \forall \ k = 1, \dots, K \end{cases}$$

- The objective is **pseudo-concave**.
- A local maximum is also a global maximum and KKT conditions are necessary and sufficient.

C. Isheden, Z. Chong, E. Jorswieck, G. Fettweis, "Framework for Link-Level Energy Efficiency Optimization with Informed Transmitter", IEEE Trans. on Wireless Communications, vol. 11, no. 8, pp. 2946-2957, Aug. 2012.

Parametric approach: Dinkelbach's algorithm

Consider the function

$$F(\lambda) = \max_{\boldsymbol{x}} \{ (f(\boldsymbol{x}) - \lambda g(\boldsymbol{x})) : h_k(\boldsymbol{x}) \le 0, \ \forall \ k = 1, \dots, K \}$$
 (1)

There exists a unique, positive λ^* such that $F(\lambda^*) = 0$ and an optimal solution of (1) with $\lambda = \lambda^*$ solves the CFP.

 This method allows to solve a CFP by converting it into a sequence of convex problems

• Solving a CFP is equivalent to **finding the zero** of the function $F(\lambda)$.

```
Dinkelbach's algorithm  \epsilon > 0; \ n = 0; \ \lambda_n = 0;  repeat  x_n^* = \arg\max_{\boldsymbol{x}} \left\{ f(\boldsymbol{x}) - \lambda_n g(\boldsymbol{x}) \ : \ h_k(\boldsymbol{x}) \leq 0 \ , \ \forall \ k = 1, \dots, K \right\};   F(\lambda_n) = f(\boldsymbol{x}_n^*) - \lambda_n g(\boldsymbol{x}_n^*);   \lambda_{n+1} = \frac{f(\boldsymbol{x}_n^*)}{g(\boldsymbol{x}_n^*)};   n = n+1;  until F(\lambda_n) < \epsilon
```

W. Dinkelbach, "On nonlinear fractional programming," Management Science, vol. 13, no. 7, pp. 492 - 498, March 1967

Insights into Dinkelbach's algorithm

The update rule for λ follows Newton's method.

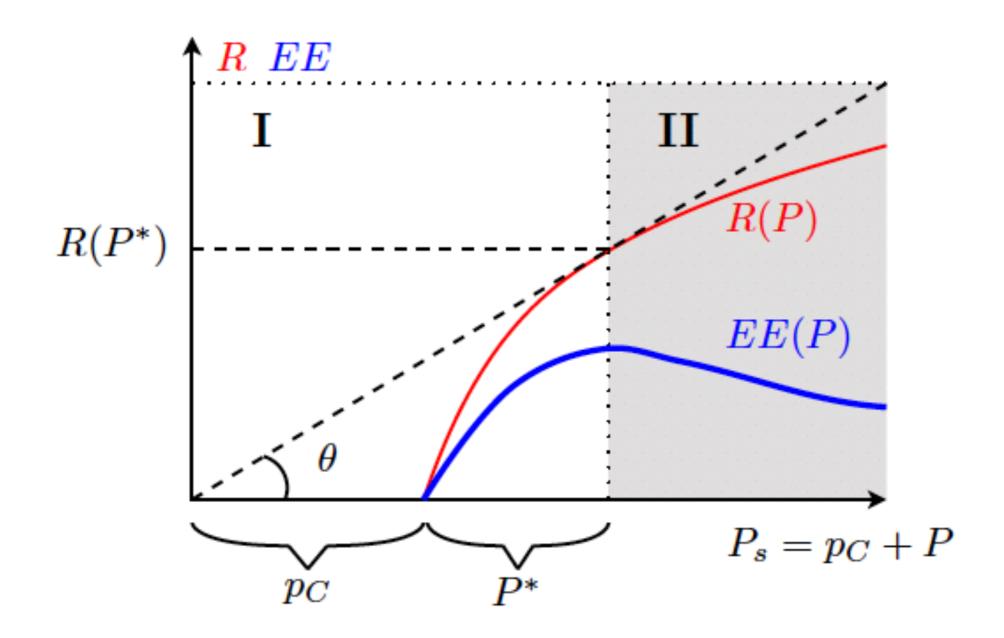
$$\lambda_{n+1} = \lambda_n - \frac{F(\lambda_n)}{F'(\lambda_n)} = \lambda_n - \frac{f(\mathbf{x}_n^*) - \lambda_n g(\mathbf{x}_n^*)}{-g(\mathbf{x}_n^*)} = \frac{f(\mathbf{x}_n^*)}{g(\mathbf{x}_n^*)}$$

- Super-linear convergence rate.
- The algorithm works for general FP, too. However, we have to compute F(λ)...
- ... if the problem is not a CFP, we can still use Dinkelbach, but in each iteration we need to globally solve a non-convex problem

$$F(\lambda) = \max_{\mathbf{x}} \{ f(\mathbf{x}) - \lambda g(\mathbf{x}) : h_k(\mathbf{x}) \le 0, \forall k = 1, ..., K \}$$

Application

Energy-Efficient Power Control in 5G



Power Control for Energy Efficiency

- Power control for energy efficiency can be performed in a centralized or decentralized manner. Both approaches are of interest in the context of 5G networks, for which
 - network centric techniques like Cloud-RAN and cooperative multipoint (CoMP) [1], as well as
 - user-centric techniques like device-to-device (D2D) [2] and the use of femto-cells [3], have been proposed.
- [1] D. Gesbert, S. Hanly, H. Huang, S. Shamai Shitz, O. Simeone, and W. Yu, "Multicell MIMO cooperative networks: A new look at interference," IEEE J. Sel. Areas Commun., vol. 28, no. 9, Dec. 2010.
- [2] F. Boccardi, R. W. H. Jr., A. Lozano, T. L. Marzetta, and P. Popovski, "<u>Five</u> disruptive technology directions for 5G," IEEE Communications Magazine, vol. 52, no. 2, pp. 74–80, February 2014.
- [3] J. Hoydis, M. Kobayashi, and M. Debbah, "Green small-cell networks," IEEE Vehicular Technology Magazine, vol. 6, no. 1, pp. 37 43, March 2011.

Network-centric GEE Model

SINR of transmitter *k* on resource *n*

received signal power channel gain times transmit power

$$\gamma_{k,n} = \frac{\alpha_{k,n} p_{k,n}}{\sigma_{k,n}^2 + \phi_{k,n} p_{k,n} + \sum_{j \neq k} \omega_{kj,n} p_{j,n}}$$

noise power

self-interference

interference from other active links

bandwidth

SINR tx k rs n

Global energy efficiency

$$\psi \triangleq \frac{\sum_{k=1}^{K} \sum_{n=1}^{N} B \log_2 (1 + \gamma_{k,n})}{p_c + \sum_{k=1}^{K} \mathbf{1}^T \mathbf{p}_k}$$

total circuit power dissipated

transmit power allocation

Applications to 5G Technologies I

- Massive MIMO (uplink, S cells, M antennas, K users)
 - Channel of UE j in cell l to BS i: \mathbf{h}_{ilj}
 - MMSE-based channel estimation
 - SINR expression holds with

$$\alpha_k = \rho_{iik}^2 , \quad \omega_{kj} = d_{ilj}\rho_{iik}$$
$$\phi_k = d_{iik}\rho_{iik} + \sum_{l \neq i} \rho_{ilk}^2$$

large scale fading

$$\rho_{iik} = \frac{d_{iik}}{\tau + \sum_l d_{ilk}}$$
 pilot sequence parameter

J. Hoydis, S. ten Brink, and M. Debbah, "<u>Massive MIMO in the UL/DL of cellular networks: How many antennas do we need?</u>" IEEE Journal on Selected Areas in Communications, vol. 31, no. 2, pp. 160 – 171, February 2013.

Applications to 5G Technologies II

- Two-hop multi-point to multi-point network with S BSs with M antennas using N subcarriers, K UEs, exploiting a SISO AF relay.
- SINR model applies with $\sigma_{k,n}^2 = \sigma_n^2(p_{r,n}|\mathbf{c}_{k,n}^H\mathbf{h}_{i_k,n}|^2 + \sigma_{i_k,n}^2\|\mathbf{c}_{k,n}\|^2)$

$$\alpha_{k,n} = p_{r,n} |h_{k,n}|^2 |\mathbf{c}_{k,n}^H \mathbf{h}_{i_k,n}|^2, \quad \phi_{k,n} = \sigma_{i_k,n}^2 |h_{k,n}|^2 ||\mathbf{c}_{k,n}||^2$$

$$\omega_{kj,n} = \left(p_{r,n} |\mathbf{c}_{k,n}^H \mathbf{h}_{i_k,n}|^2 + \sigma_{i_k,n}^2 ||\mathbf{c}_{k,n}||^2 \right) |h_{j,n}|^2$$

A. Zappone, E. A. Jorswieck, and S. Buzzi, "Energy efficiency and interference neutralization in two-hop MIMO interference channels," IEEE Transactions on Signal Processing, vol. 62, no. 24, pp. 6481–6495, December 2014.

Y. Pei and Y.-C. Liang, "Resource allocation for device-to-device communications overlaying two-way cellular networks," IEEE Transactions on Wireless Communications, vol. 12, no. 7, pp. 3611–3621, July 2013.

Centralized Algorithm for N=1

• GEE optimal power control: max

$$\max_{\mathbf{p} \in \mathcal{P}} \frac{\sum_{k=1}^{K} B \log_2 (1 + \gamma_k)}{p_c + \sum_{k=1}^{K} p_k}$$

Feasibility

Let $\mathbf{F} \in \mathbb{C}^{K \times K}$ be a matrix whose (k, j)-th element is defined as

$$[\mathbf{F}]_{k,j} \triangleq \begin{cases} 0 & j = k \\ \frac{\omega_{kj}\underline{\gamma}_k}{\alpha_k - \phi_k\underline{\gamma}_k} & j \neq k \end{cases}$$
 (1)

and denote by $\rho_{\mathbf{F}}$ its spectral radius. The solutions to GEE problems exist if and only if

$$\rho_{\mathbf{F}} < 1 \quad \text{and} \quad (\mathbf{I} - \mathbf{F})^{-1} \, \underline{\mathbf{s}} \le \overline{\mathbf{p}}$$
(2)

where $\overline{\mathbf{p}} = [\overline{p}_1, \overline{p}_2, \dots, \overline{p}_K]^T \in \mathbb{R}_+^{K \times 1}$ and $\mathbf{s} \in \mathbb{R}_+^K$ has elements given by $[\underline{\mathbf{s}}]_k \triangleq \sigma_k^2 \underline{\gamma}_k (\alpha_k - \phi_k \underline{\gamma}_k)^{-1}$.

First-order Optimal Solution by Sequential Convex Programming

The general idea of sequential convex programming is to find **local optima of a difficult problem** with objective f to maximize, by **solving a sequence of easier problems** with objectives f_i

1.
$$f_i(\mathbf{x}) \leq f(\mathbf{x})$$
, for all \mathbf{x} ;

2.
$$f_i(\mathbf{x}^{(i-1)}) = f(\mathbf{x}^{(i-1)});$$

3.
$$\nabla f_i(\mathbf{x}^{(i-1)}) = \nabla f(\mathbf{x}^{(i-1)}).$$

Bound $\log_2(1+\gamma) \ge a \log_2 \gamma + b$ works well and **iterative** algorithm can be developed that **converges** to stationary point

- B. R. Marks and G. P. Wright, "A general inner approximation algorithm for nonconvex mathematical programs," Operations Research, vol. 26, no. 4, pp. 681–683, July-Aug. 1978.
- M. Chiang, C. Wei, D. P. Palomar, D. O'Neill, and D. Julian, "Power control by geometric programming," IEEE Trans. Wireless Commun., vol. 6, no. 7, pp. 2640–2651, Jul. 2007.
- L. Venturino, N. Prasad, and X. Wang, "Coordinated scheduling and power allocation in downlink multicell OFDMA networks," IEEE Trans. Veh. Technol., vol. 58, no. 6, pp. 2835–2848, Jul. 2009.
- D. Nguyen, L.-N. Tran, P. Pirinen, and M. Latva-aho, "Precoding for full duplex multiuser MIMO systems: Spectral and energy efficiency maximization," IEEE Transactions on Signal Processing, vol. 61, no. 16, pp. 4038 4050, Aug 2013.

User-centric EE Model

- Game theoretic approach $\mathcal{G} \triangleq \{\mathcal{K}, \{\mathcal{P}_k(\mathbf{p}_{-k})\}_k, \{\mathrm{EE}_k(p_k, \mathbf{p}_{-k})\}_k\}$
- Best response of user k

$$\max_{\mathbf{p}_k \in \mathcal{P}_k} \quad \text{EE}_k = \max_{\mathbf{p}_k \in \mathcal{P}_k} \quad \frac{\sum_{n=1}^N B \log_2(1 + \gamma_{k,n})}{p_{c,k} + \mathbf{1}^T \mathbf{p}_k} \quad \forall k.$$

- 1. The game has non-empty set of GNE points.
- 2. The game G admits a **unique GNE point**, which can be obtained by starting from any feasible power playing the BRD.
- 3. The BRD can be **implemented** in **distributed** way exploiting the Dinkelbach algorithm from fractional programming.

Numerical

 \blacksquare (a) Algorithm 1. R = 20%

 \leftarrow (b) Algorithm 1. R = 0%

-35

+ (d) Maximum power allocation

-30

→ (c) Algorithm 1 for sum-rate maximization

-25

 \overline{P} [dBW]

-20

-15

-10

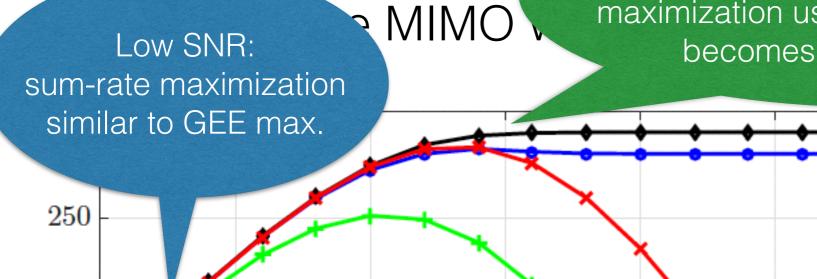
200

100

-40

 $[\mathrm{Mbit}/\mathrm{J}]$

High SNR: (a) uses some power to satisfy rate constraints, (c) sum rate maximization uses too much power and becomes energy inefficient.



$$K = 5, M = 50, \tau = 10^{-2}$$

 $B = 1 \text{MHz}$

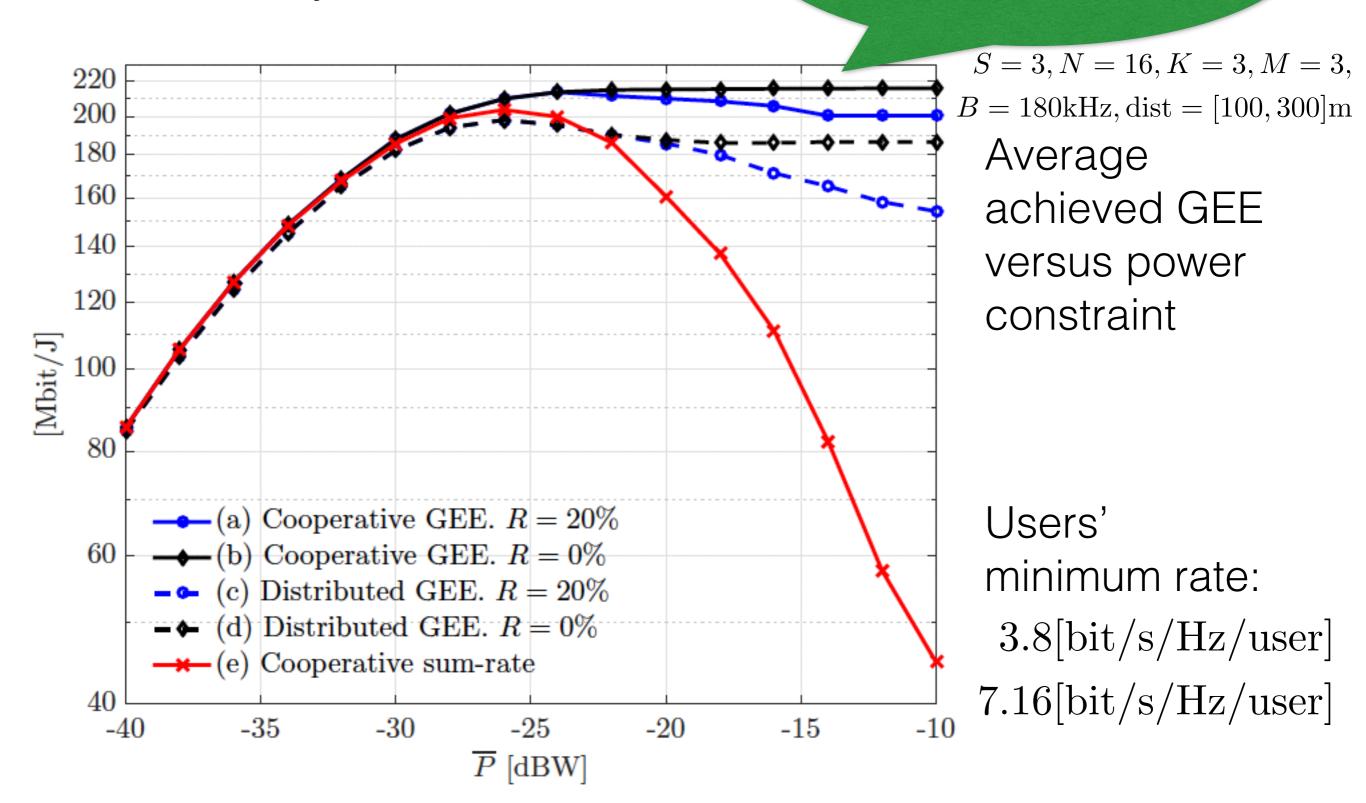
Average achieved GEE versus power constraint

Algorithm 1 is centralized optimizing GEE

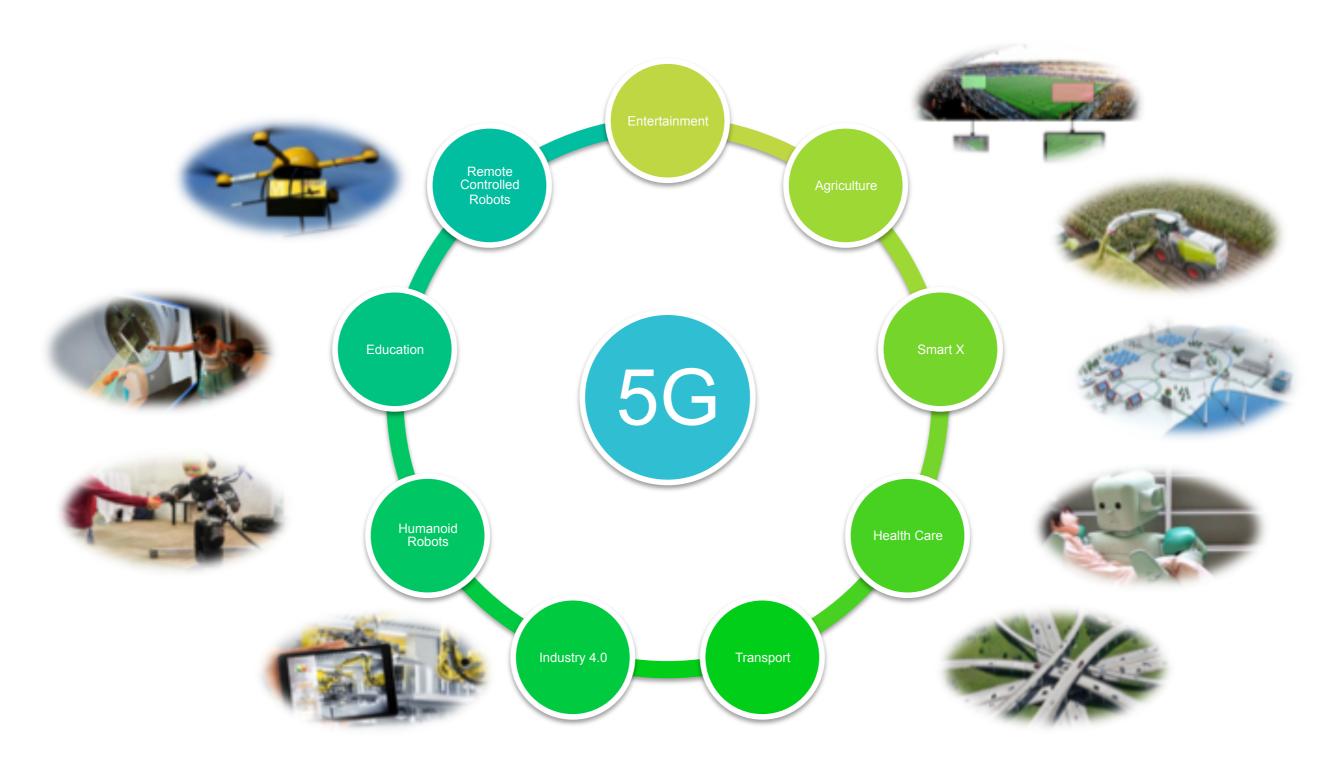
Numerical Distributation

Relay-assisted OFDMA in

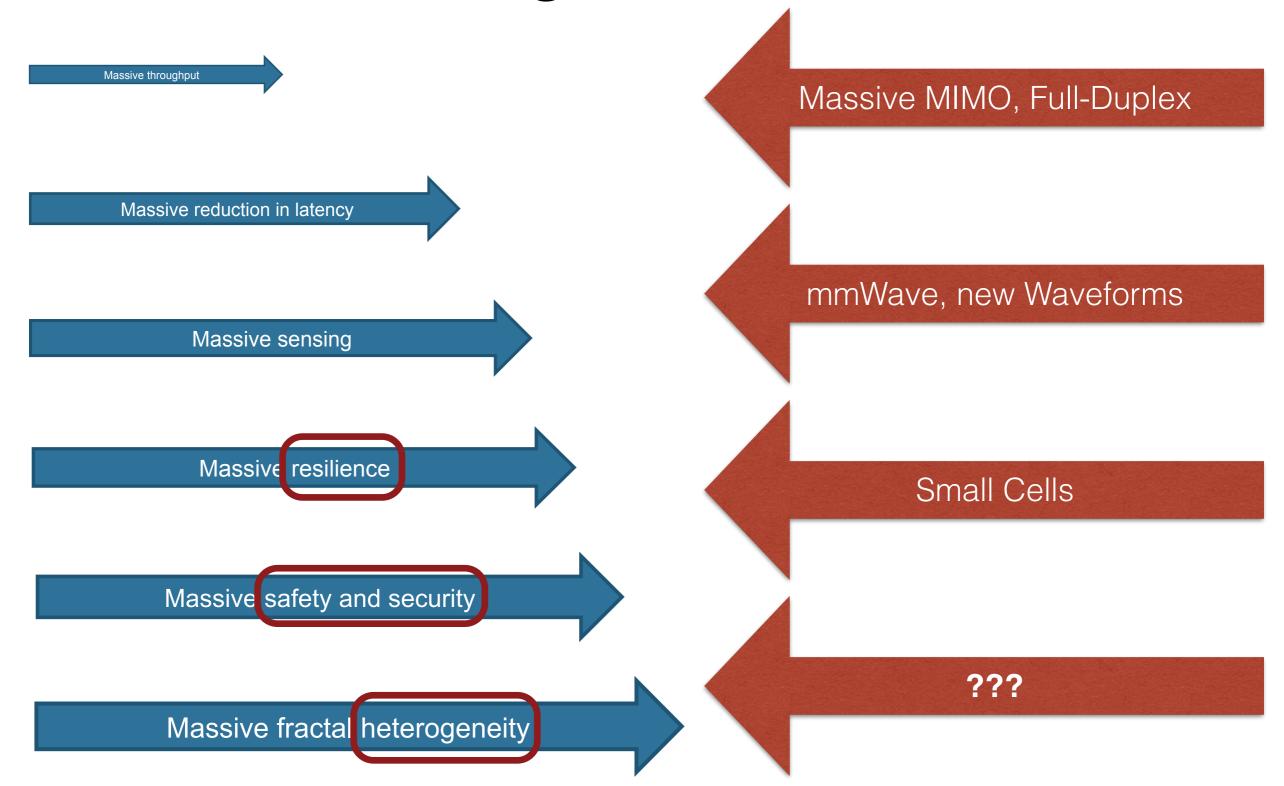
Low Price of Anarchy because of many resources and few users



Conclusions



Challenges - Solutions



Challenges - Solutions

Massive throughput Massive MIMO, Full-Duplex Massive reduction in latency mmWave, new Waveforms Massive sensing Massive resilience Small Cells Massive safety and security **Multi-Objective Optimization** Massive fractal heterogeneity

Conclusions

- The fifth and subsequent generations of mobile communications introduce a number of **massive requirements** in terms of *throughput* and *efficiency* improvement, reduction in *latency*, *scaling* with large number of devices, *robustness* and *resilience*, *safety* and *security*, as well as *heterogeneity*.
- Some of the goals (e.g. the throughput improvement) will be achieved by **new technologies**, e.g., massive MIMO, full duplex, mmWave, new waveforms, adaptive flexible spectrum management.
- Other important requirements as heterogeneity, efficiency, security are to be achieved by new systematic solution concepts (e.g. multi-objective optimization, fractional programming).

References

- A. Zappone and E. Jorswieck, "Energy Efficiency in Wireless Networks via Fractional Programming Theory". Foundations and Trends in Communications and Information Theory, vol. 11, no. 3-4, June 2015, pp. 185-396.
- A. Zappone, F. Di Stasio, S. Buzzi, E. Jorswieck, "Sequential Fractional Programming for Energy-Efficient Resource Allocation in 5G Networks: General Theory and a Case Study based on Device-to-Device Underlay", John Wiley & Sons, to appear 2015.
- A. Zappone, L. Sanguinetti, G. Bacci, E. Jorswieck, M. Debbah, "Energy-Efficient Power Control: A Look at 5G Wireless Technologies", IEEE Trans. on Signal Processing, will appear 2016.
- E. Björnson, E. Jorswieck, M. Debbah, B. Ottersten, "Multi-Objective Signal Processing Optimization: The Way to Balance Conflicting Metrics in 5G Systems",
 IEEE Signal Processing Magazine, vol. 31, no. 6, pp. 14-23, Nov. 2014.

Thank you for your attention!



Backup Slides

Computational Complexity

Table II

 $K=5; M=50; \tau=10^{-2}$. Average number of required iterations to reach convergence versus P_{max} for: (a) Algorithm 1 for GEE maximization with R=20%; (b) Algorithm 1 for GEE maximization with R=0%; (c) Algorithm 2 for distributed resource allocation with R=0%.

	Maximum power \overline{P} [dBW]							
	$\overline{P} = -38$	$\overline{P} = -34$	$\overline{P} = -30$	$\overline{P} = -26$	$\overline{P} = -22$	$\overline{P} = -18$	$\overline{P} = -14$	$\overline{P} = -10$
Algorithm 1. $R = 0\%$	2.63	3.69	4.68	6.30	6.53	6.49	6.50	6.51
Algorithm 1. $R = 20\%$	2.63	3.67	4.87	6.68	6.70	6.76	6.76	6.77
Algorithm 2. $R = 0\%$	1	1.01	1.07	1.42	2.54	3.66	4.12	4.50
Algorithm 2. $R = 20\%$	1	1.01	1.07	1.42	2.54	3.67	4.19	6.71

- Centralized Algorithm has polynomial complexity (in K and N).
- Decentralized Algorithm has polynomial complexity, too. (in N, scales linearly with K)

5G - Massive Requirements

Massive throughput

Massive reduction in latency

Massive sensing

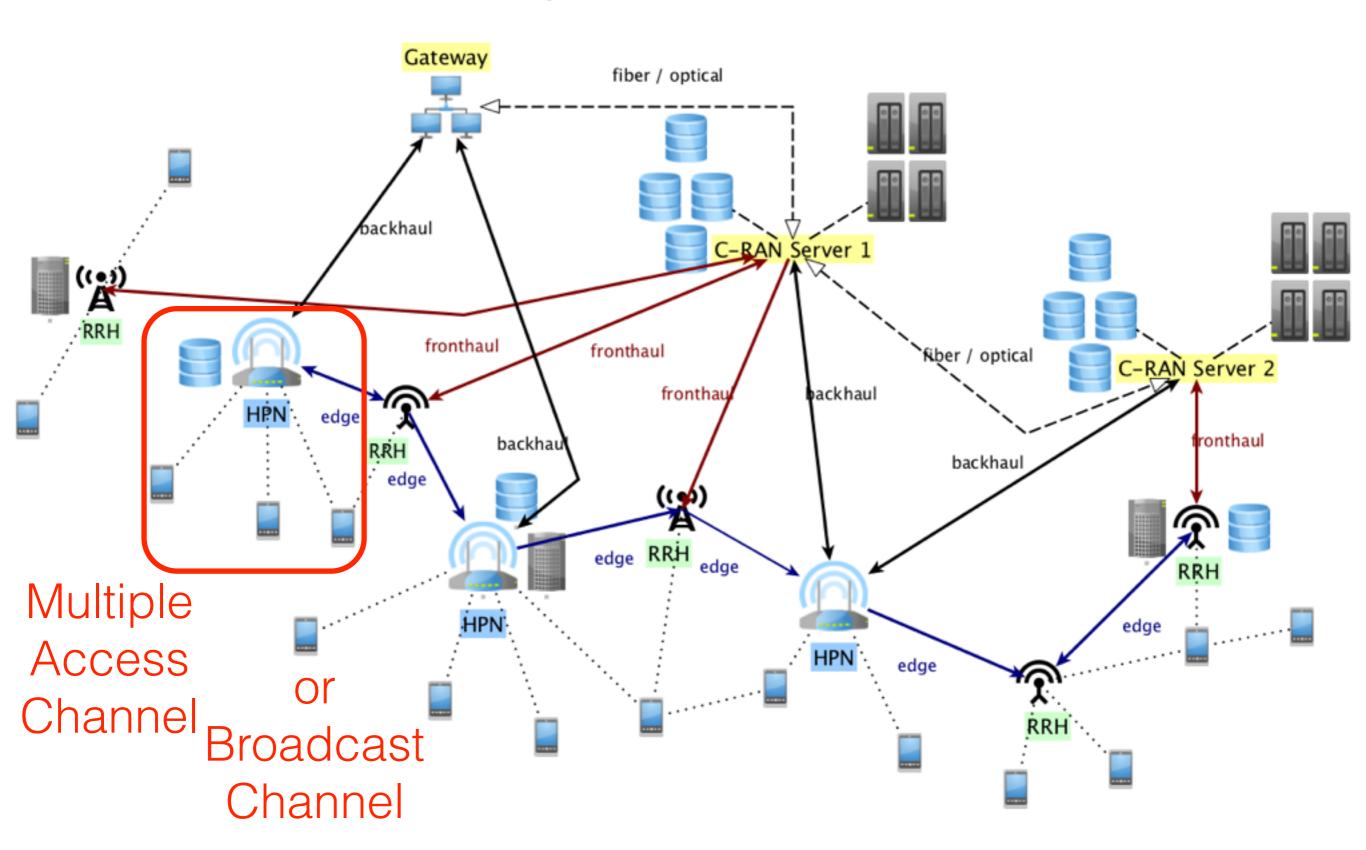
Massive resilience

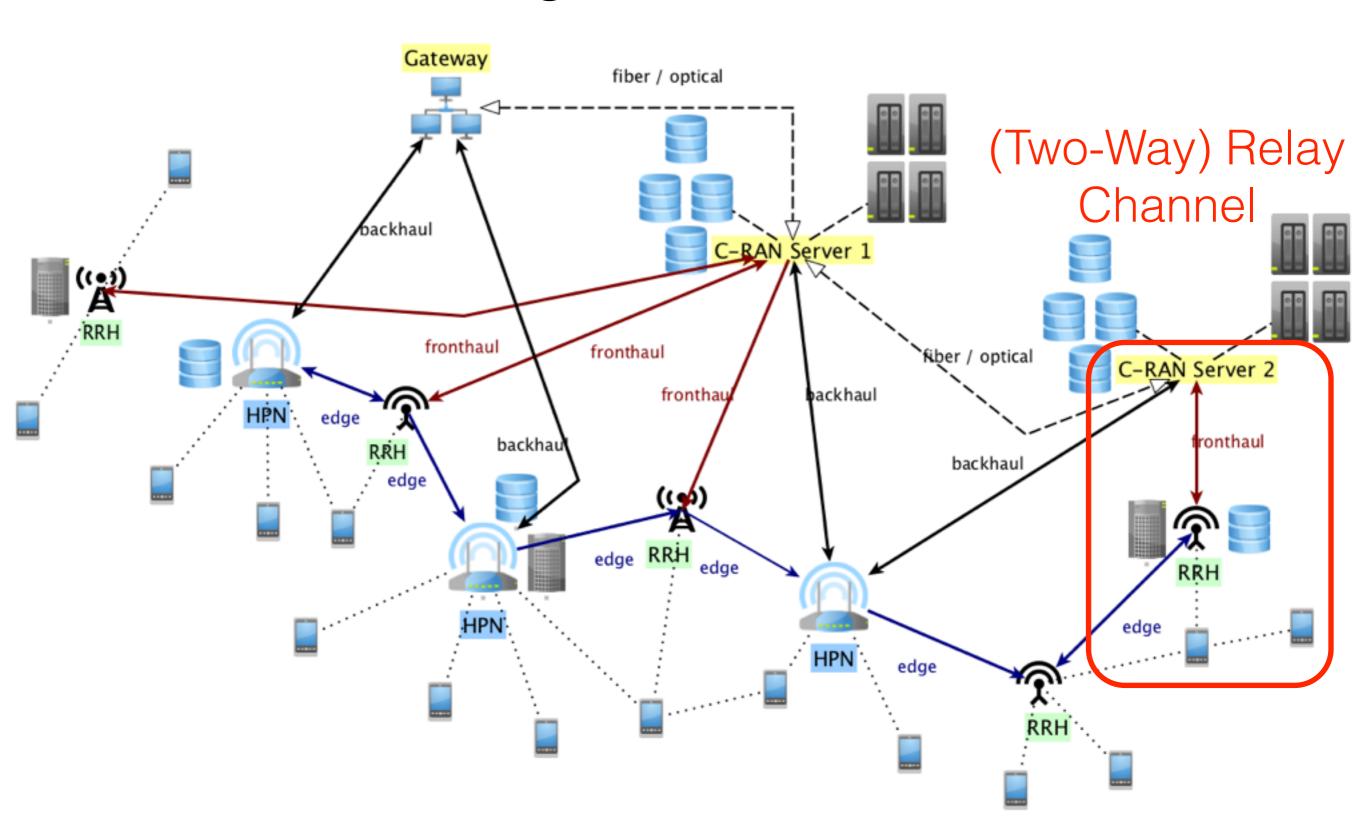
Massive safety and security

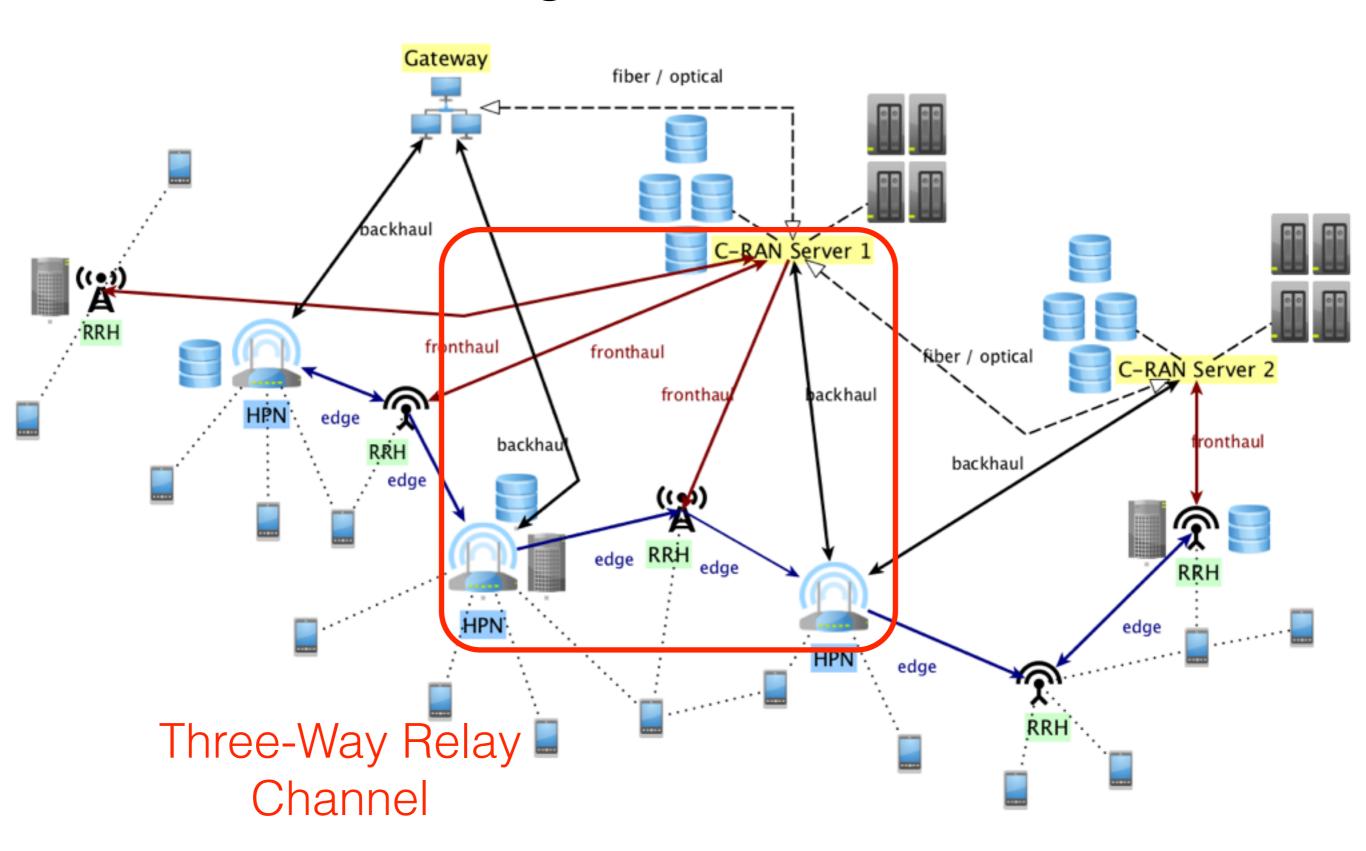
Massive fractal heterogeneity

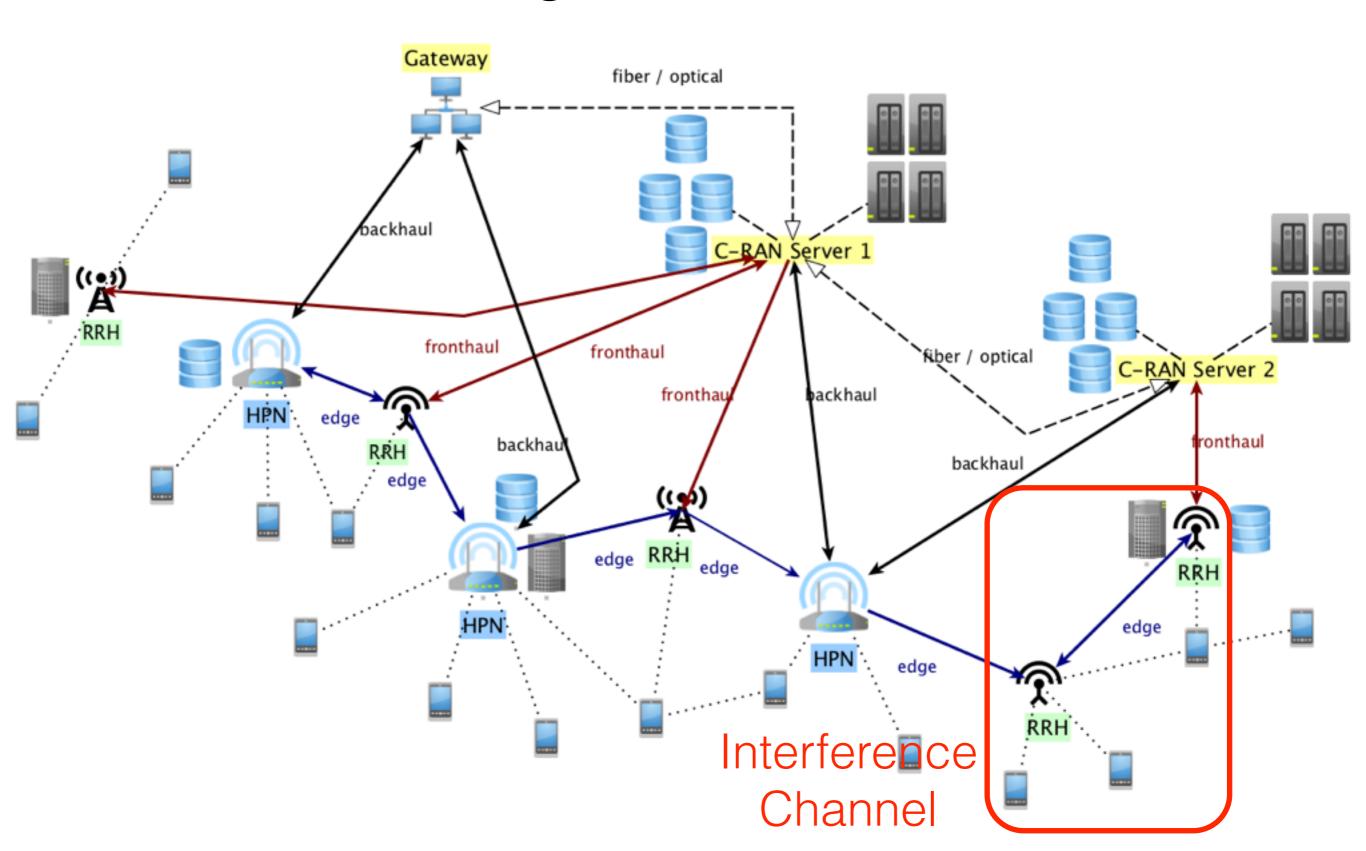
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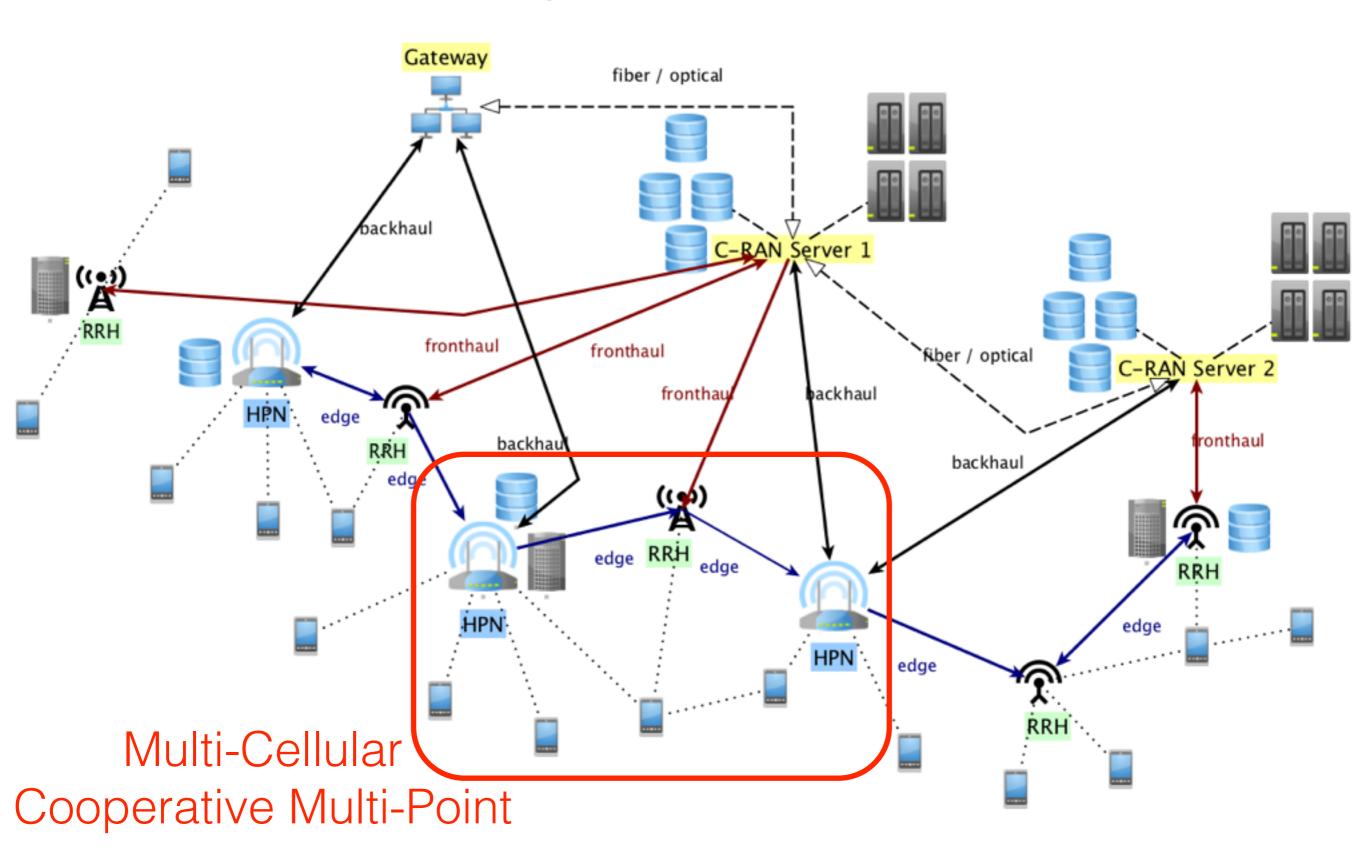


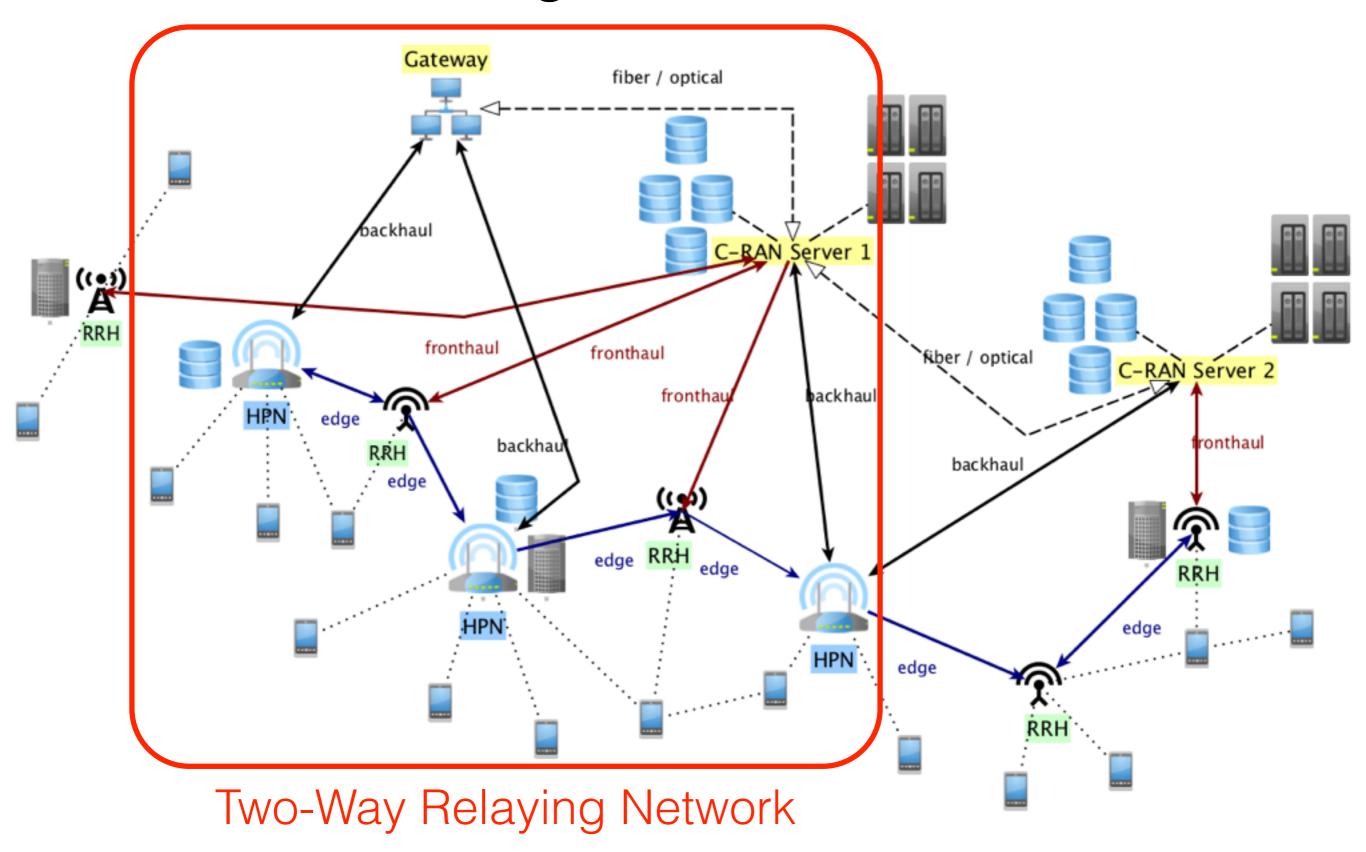




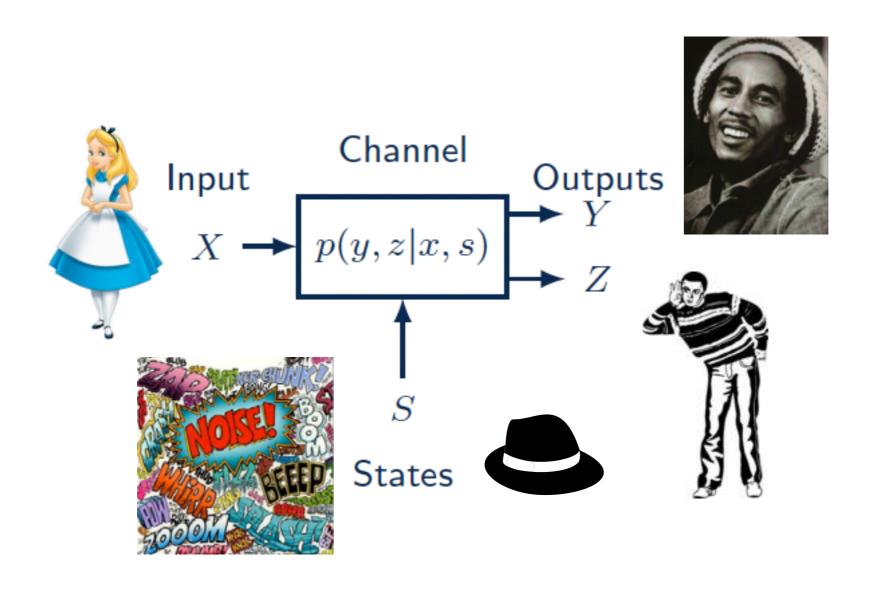






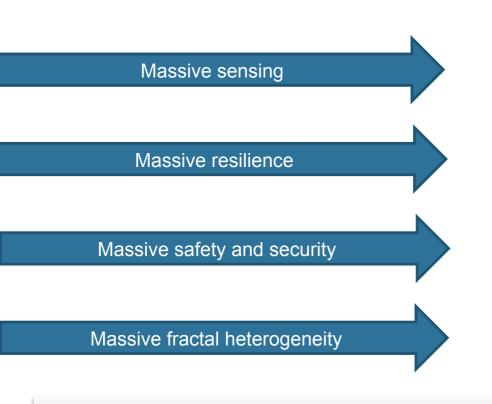


Applications 2 Physical Layer Security



Motivation for Physical Layer Security

- Large number of connected devices.
- Cryptographic solutions to confidentiality or authentication do not scale
- Physical layer security provides unconditional security (information theoretic security)



Secure communications

Secret key generation

Wireless authentication

E. Jorswieck, S. Tomasin, A. Sezgin, "Broadcasting into the Uncertainty: Authentication and Confidentiality by Physical Layer Processing", Proceedings of IEEE, vol. 103, no. 10, pp. 1702-1724, Oct. 2015.

Confidentiality Measures

- Whatever the adversary overhears, it should not contain any information about the message.
- Information Theoretic Confidentiality Measures

New Objective Function or Additional Constraints in MOP

Instantaneous

Sequence (strong)

$$I(M;z) \le \epsilon$$

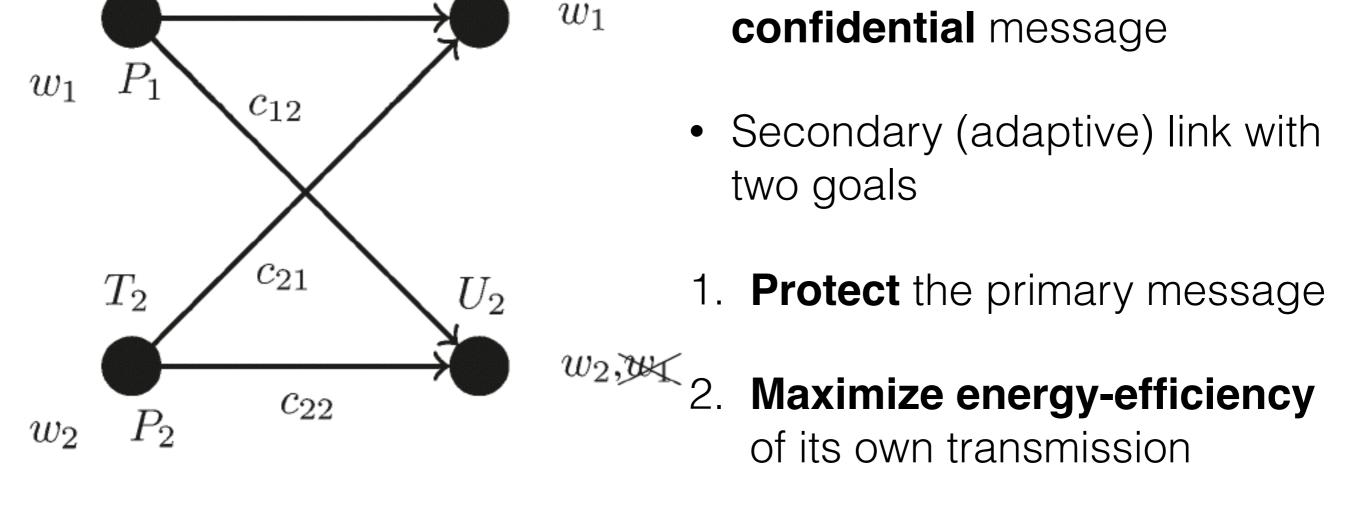
$$\frac{1}{n}I(M;\mathbf{z}^n) \le \epsilon$$

$$I(M; \mathbf{z}^n) \leq \epsilon$$

$$\max_{m,m'} \mathbb{V}(p_{\mathbf{z}^n|M=m}, p_{\mathbf{z}^n|M=m'}) < \epsilon$$

Interference Channel with Secrecy Constraints

 T_1



Primary (legacy) link with

F. Gabry, A. Zappone, R. Thobaben, E. Jorswieck, M. Skoglund, "Energy Efficiency Analysis of Cooperative Jamming in Cognitive Radio Networks with Secrecy Constraints", IEEE Wireless Communications Letters, vol. 4, no. 4, pp. 437-440, Aug. 2015.

Preliminaries & Problem Statement

Achievable rate region under cooperative jamming:

$$R_{1} < \left(C\left(\frac{P_{1}}{1 + c_{21}P_{2}}\right) - C\left(\frac{c_{12}P_{1}}{1 + c_{22}\rho P_{2}}\right)\right)^{+},$$

$$R_{2} < C\left(\frac{c_{22}(1 - \rho)P_{2}}{1 + c_{12}P_{1} + c_{22}P_{2}\rho}\right).$$

 Maximize secondary user energy-efficiency under primary user secrecy constraints

$$\max_{\rho, P_2} \frac{R_2}{\mu P_2 + P_C}$$
s.t. $R_1 \ge R_1^{WT} \text{ and } P_2 \le P_2^{max}$

F. Gabry et al., "On the optimization of the secondary transmitter's strategy in cognitive radio channels with secrecy," IEEE J. Sel. Areas Commun., vol. 32, no. 3, pp. 451–463, Mar. 2014.

Characterization of Solution

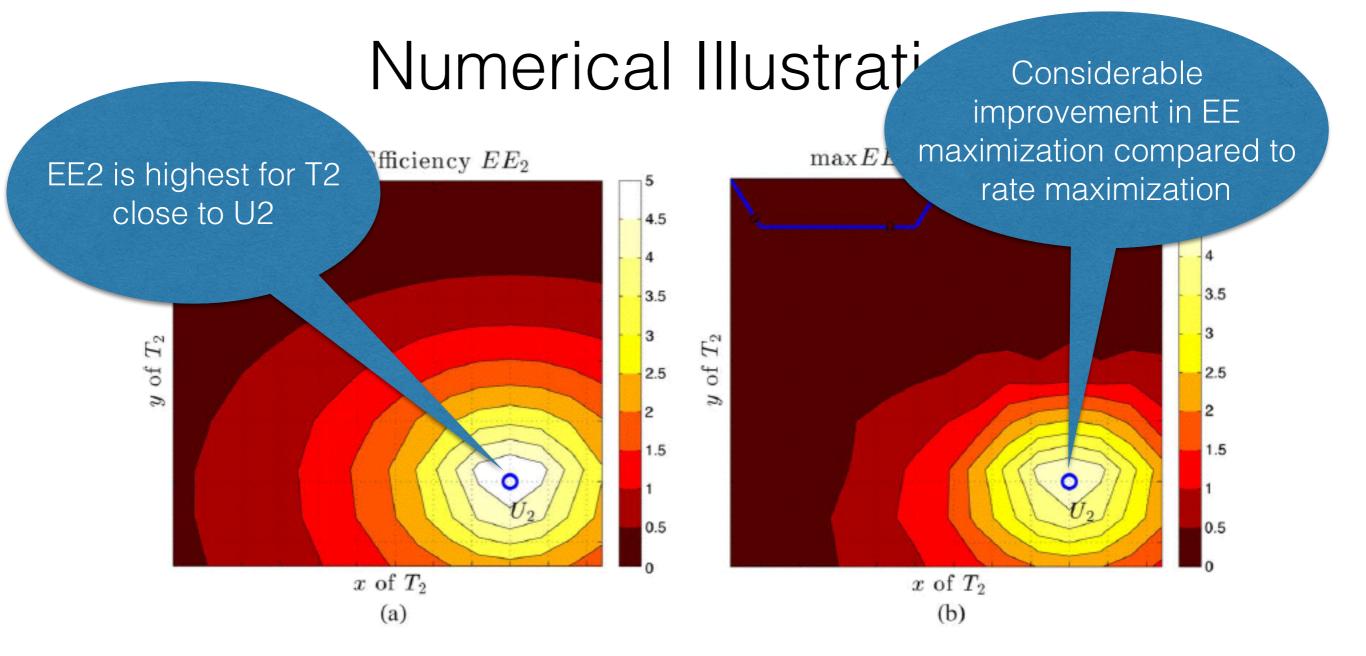
 The programming problem admits a unique solution if and only if the following condition is satisfied:

$$\frac{c_{21}(1+c_{12}P_1)}{c_{22}c_{12}(1+P_1)} < 1$$

For large transmit power this converges to

$$\frac{c_{21}}{c_{22}} < 1$$

• Intuition: Only if the channel to eavesdropper is better than to legitimate receiver, jamming is successful.



Energy efficiency analysis: (a) Secondary energy efficiency depending on the position of T2. (b) Comparison of the energy efficiency obtained from optimixation (EE2) and max R2.