

Resource Allocation in Heterogeneous Interference Networks: Energy-efficiency, Security and Latency

Eduard Jorswieck

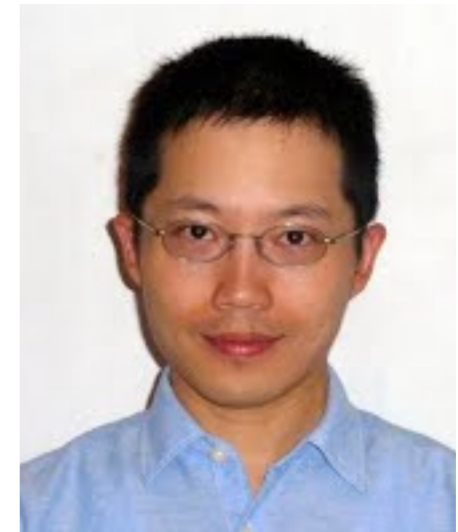


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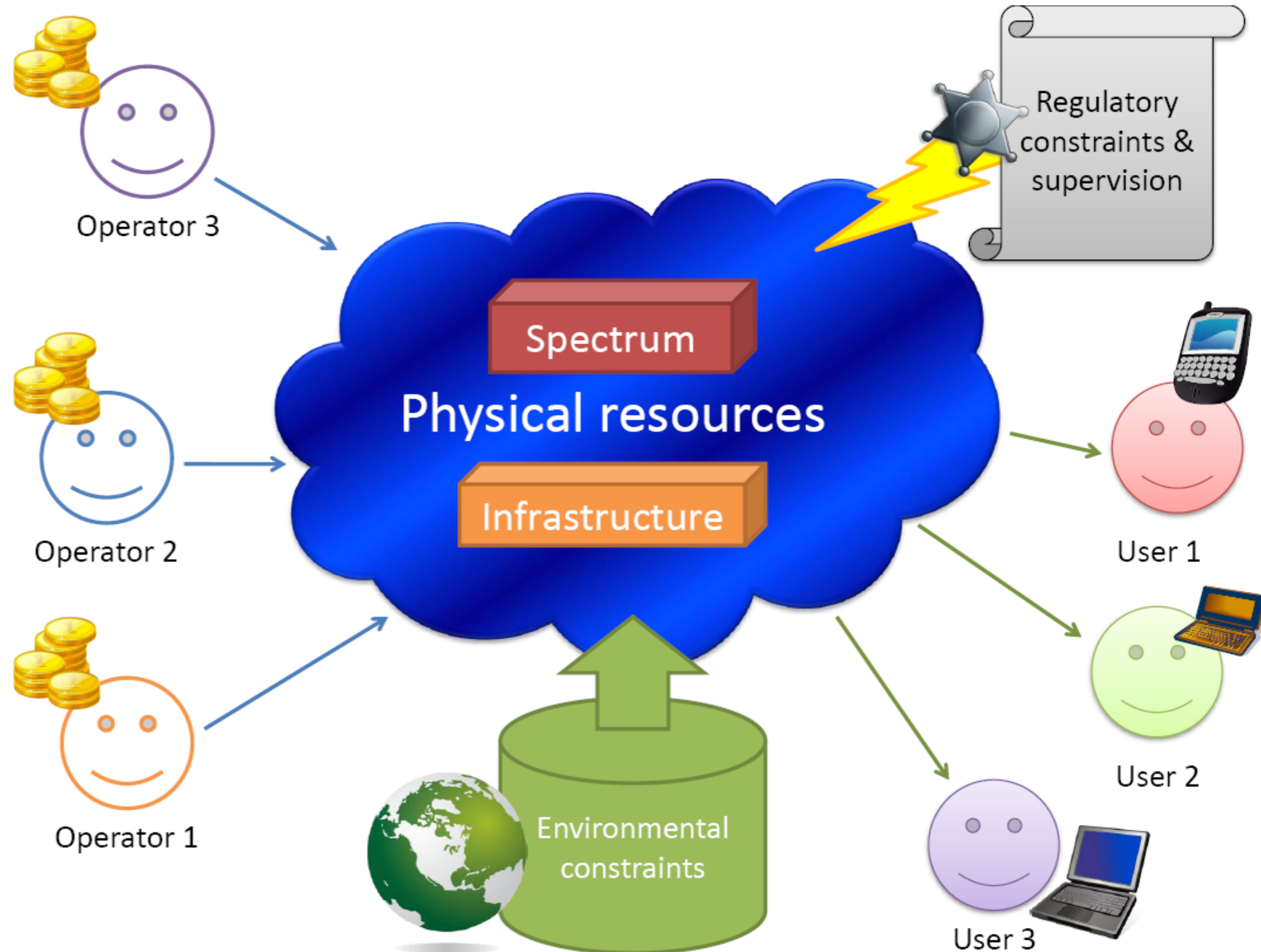
Joint work with

- Alessio Zappone (University Cassino, Italy)
- Emil Björnsson (Linköping University, Sweden)
- Pin-Hsun Lin (TU Dresden, Germany)



Resources in Wireless

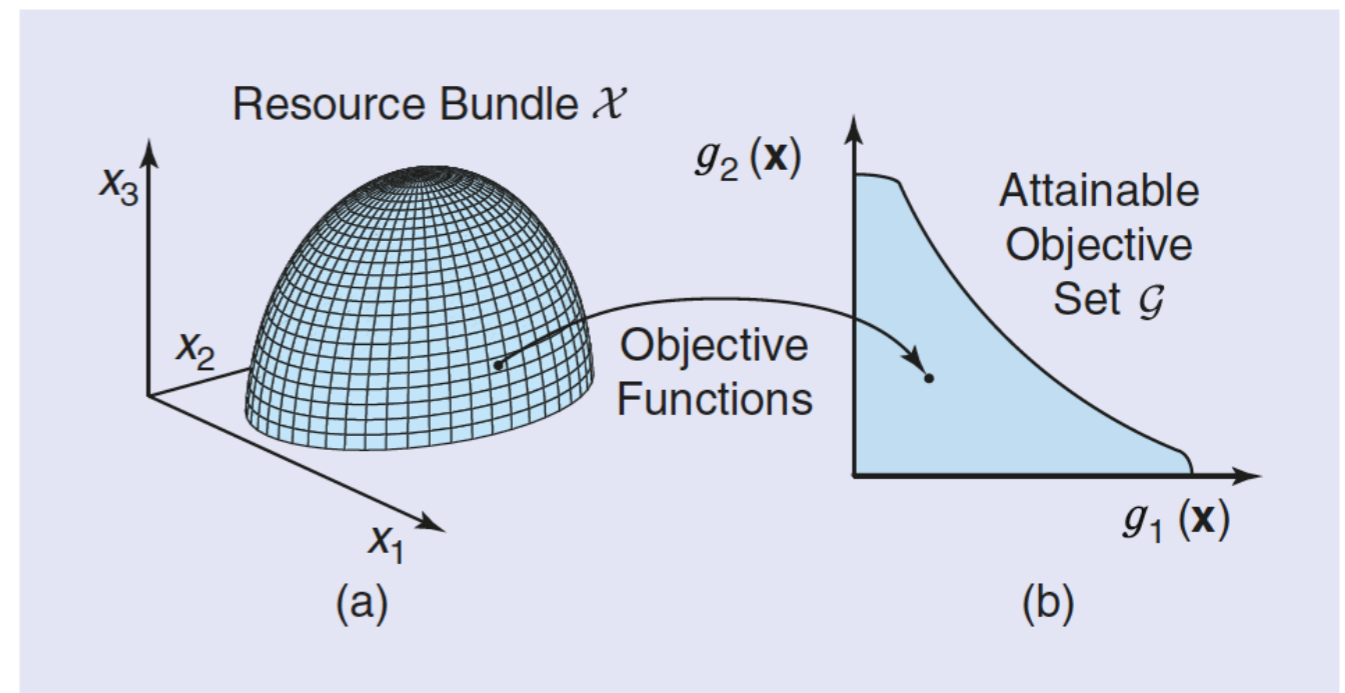
- **Spectrum**
- **Energy**
- **Infrastructure**
- **Data**
- **Computational Power**
- **Channel Info...**



Heterogeneous Services

- Conflicting performance metrics/requirements:

- Data rate / throughput
- Delay / latency
- Energy efficiency
- Security



- Multi-Objective Programming (MOP) problem

Energy-Efficiency

- The number of connected nodes will reach 50 billion by 2020 and that the **energy demand** will soon become unmanageable.
- **Bit-per-Joule energy efficiency**, defined as the amount of bits which can be reliably transmitted per Joule of consumed energy.
- Extensively studied for peaceful systems.

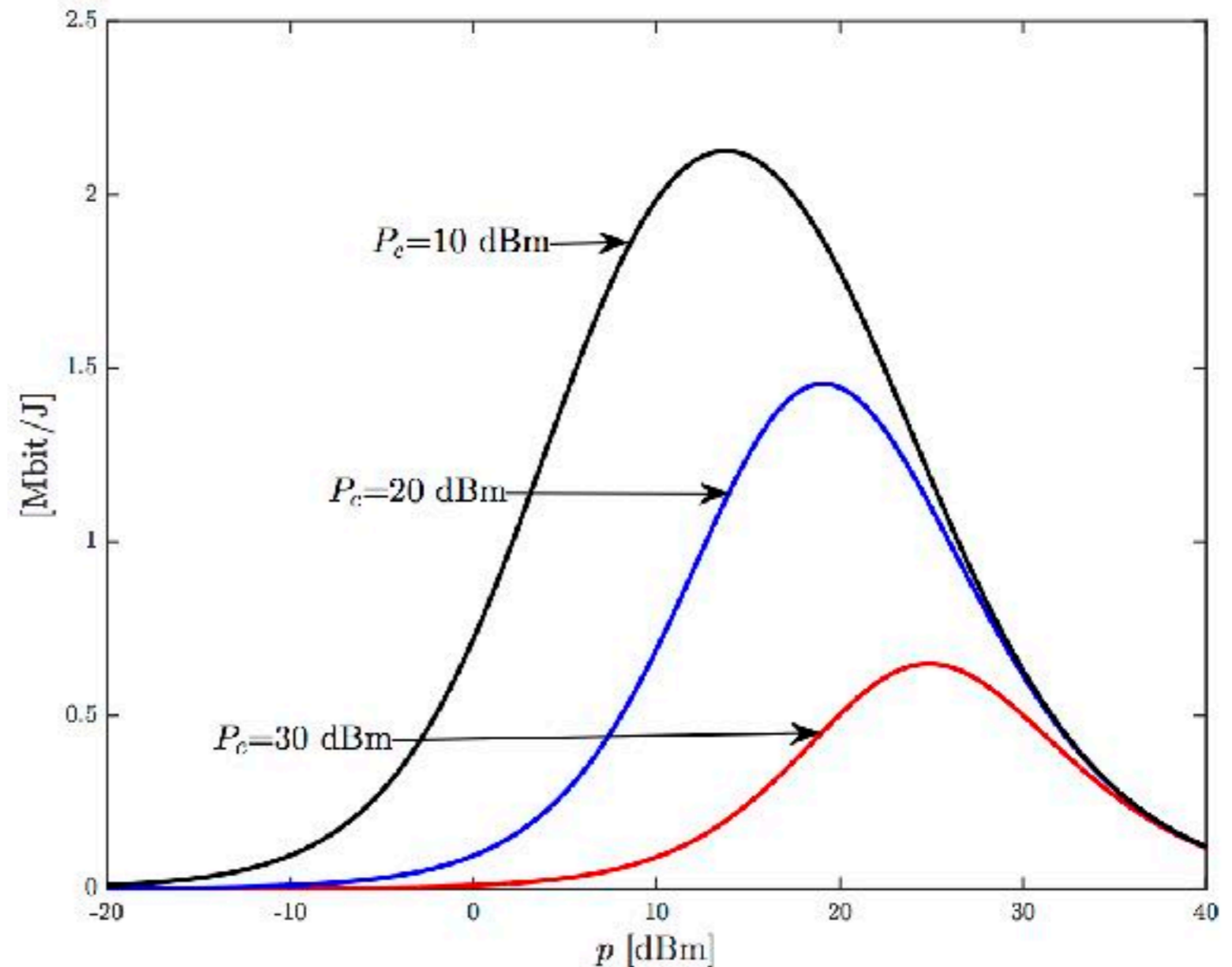
(1) G. Auer, V. Giannini, C. Desset, I. Godor, P. Skillermark, M. Olsson, M. Imran, D. Sabella, M. Gonzalez, O. Blume, and A. Fehske, "How much energy is needed to run a wireless network?" IEEE Wireless Communications, vol. 18, no. 5, pp. 40–49, Oct. 2011.

(2) D. W. K. Ng, E. S. Lo, and R. Schober, "Energy-Efficient Resource Allocation for Secure OFDMA Systems," IEEE Transactions on Vehicular Technology, vol. 61, no. 6, pp. 2572–2585, July 2012.

Energy-Efficiency

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

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.



Energy-efficiency of a network

- Global Energy-efficiency

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

- Weighted arithmetic mean

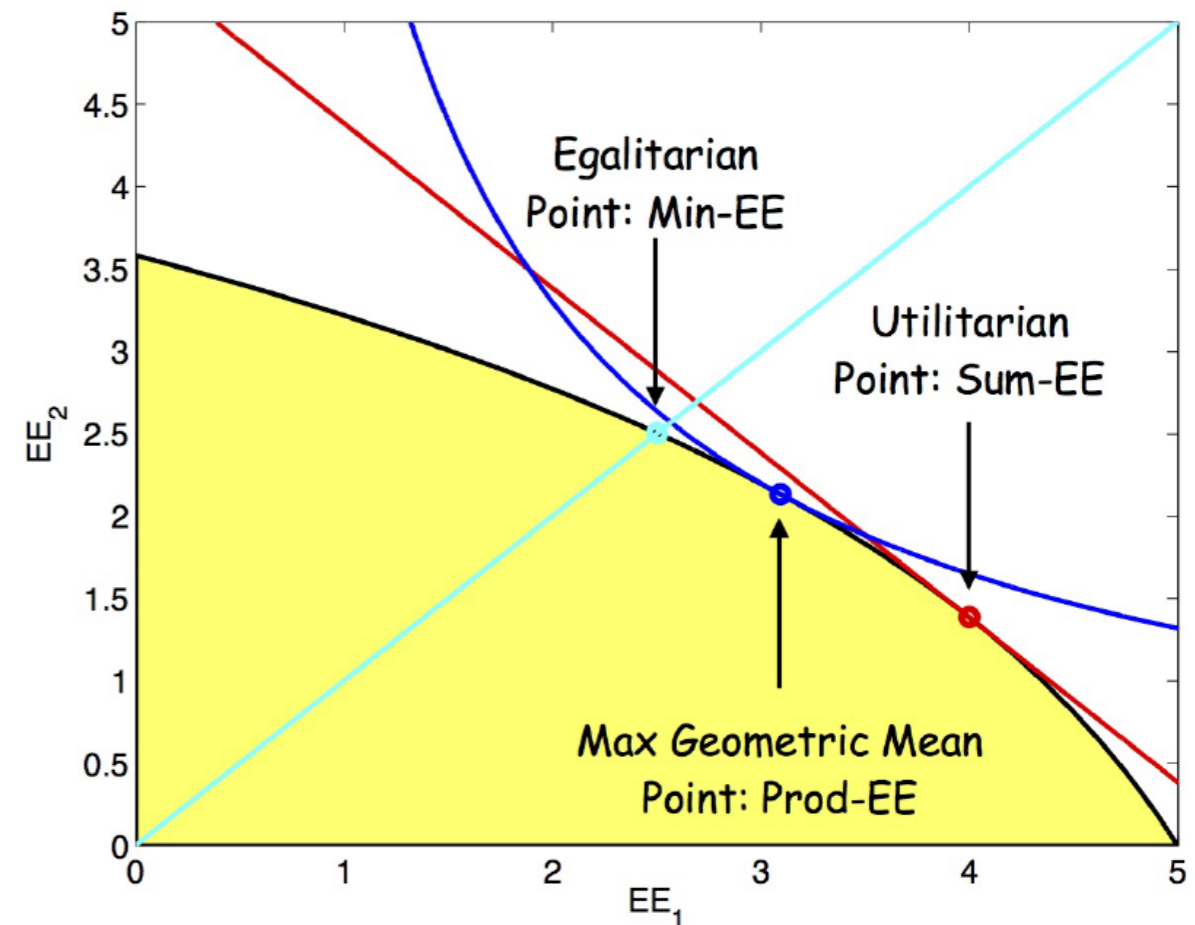
$$\text{Sum-EE} = \sum_{k=1}^K w_k \frac{f(\gamma_k(\{p_k\}_{k=1}^K))}{\alpha_k p_k + P_{c,k}}$$

- Weighted geometric mean

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

- Weighted minimum EE

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



Observation:
always ratios

Energy-efficiency of a network

- Global Energy-efficiency

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

- Weighted arithmetic mean

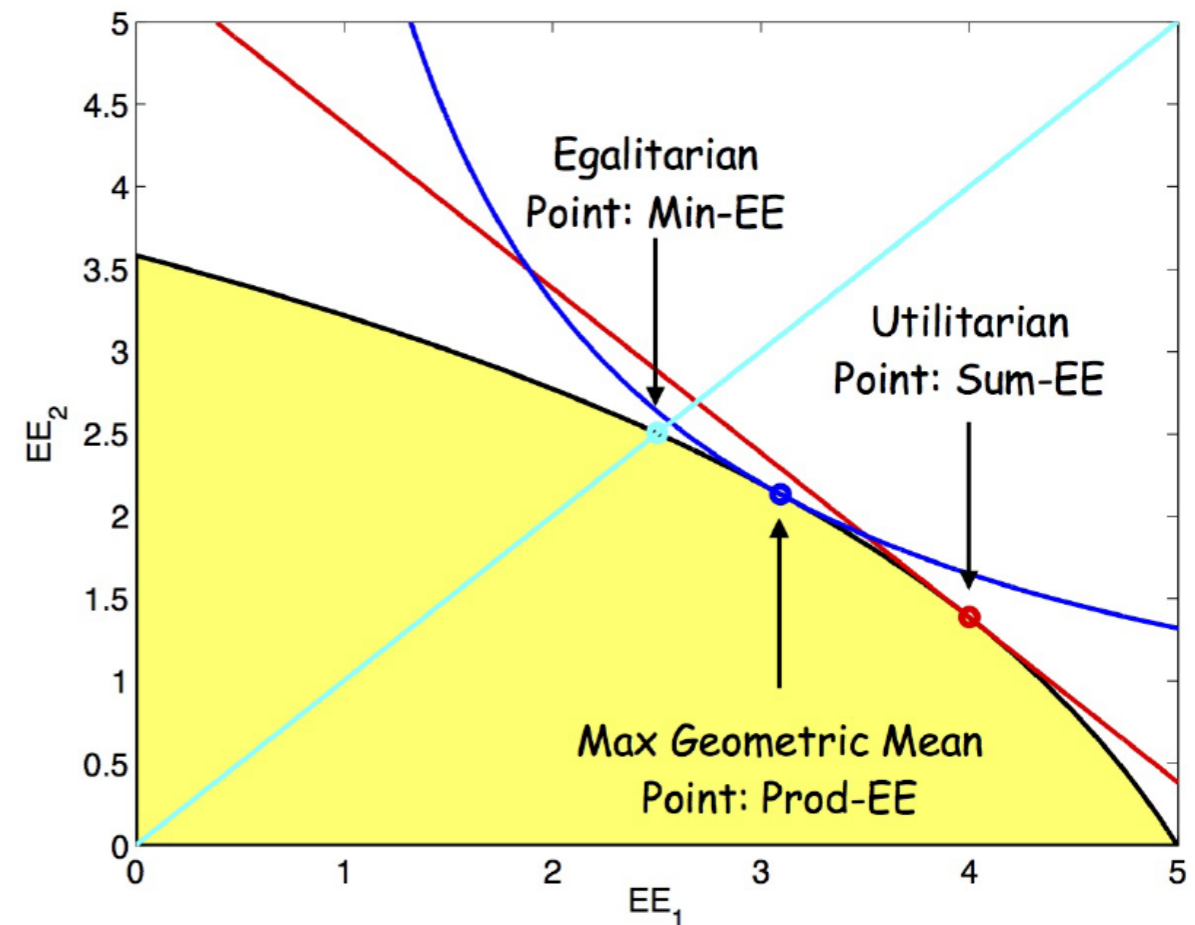
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- Weighted minimum EE

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



Observation:
always ratios

Fractional
Programming

Single ratio: concave fractional problems

CFP

$f(\mathbf{x}) \geq 0$, $g(\mathbf{x}) > 0$, differentiable functions. f , concave, g , h_k convex for all $k = 1, \dots, K$.

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

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

Parametric approach: Dinkelbach's algorithm

Consider the function

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

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 .

Dinkelbach's algorithm

```
 $\epsilon > 0; n = 0; \lambda_n = 0;$   
repeat  
   $\mathbf{x}_n^* = \arg \max_{\mathbf{x}} \{ f(\mathbf{x}) - \lambda_n g(\mathbf{x}) : h_k(\mathbf{x}) \leq 0, \forall k = 1, \dots, K \};$   
   $F(\lambda_n) = f(\mathbf{x}_n^*) - \lambda_n g(\mathbf{x}_n^*);$   
   $\lambda_{n+1} = \frac{f(\mathbf{x}_n^*)}{g(\mathbf{x}_n^*)};$   
   $n = n + 1;$   
until  $F(\lambda_n) < \epsilon$ 
```

- Superlinear convergence (Newton update)

Physical Layer Security

- Traditional cryptographic approaches for authentication, secret key generation, and confidentiality **do not scale with the number of nodes** communicating.
- Physical Layer Security introduced about 40 years ago does provide **new security primitives** to be combined with cryptographic blocks
- **Characterization of secrecy capacity** (or achievable secrecy rate) for wiretap channels is fundamental.

- (1) Y. Liang and H. V. Poor, “Multiple access channels with confidential messages,” *IEEE Trans. Inform. Theory*, vol. 54, pp. 976–1002, Mar. 2008.
- (2) I. Csiszar and J. Körner, “Broadcast channels with confidential messages,” *IEEE Trans. Inform. Theory*, vol. 24, no. 3, pp. 339–348, 1978.
- (3) A. D. Wyner, “The wiretap channel,” *Bell Syst. Tech. J.*, vol. 54, pp. 1355–1387, 1975.

Channel Uncertainty

- Challenge in providing information theoretic security is the **uncertainty** associated with the **parameters of the attacker**.
- **Statistical** (imperfect CSIT) and **deterministic** (compound and arbitrarily varying) models exist.

(1) W. Trappe, "The challenges facing physical layer security," in IEEE Communications Magazine, vol. 53, no. 6, pp. 16-20, June 2015.

(2) M. Bloch, J. Barros, M. Rodrigues, and S. McLaughlin, "Wireless information-theoretic security," IEEE Trans. Inform. Theory, vol. 54, no. 6, pp. 2515–2534, June 2008.

(3) Z. Li, R. Yates, and W. Trappe, "Achieving secret communication for fast Rayleigh fading channels," IEEE Trans. Wireless Commun., vol. 9, no. 9, pp. 2792 – 2799, Sep. 2010.

Artificial Noise

- A promising approach for statistical CSI scenarios is to **inject AN** into the channel, in order to further degrade the eavesdropper's reception on top of the secrecy coding.
- Effective way of **enhancing the secrecy** of the communication. However, **no energy efficiency analysis yet.**

- (1) S. Goel and R. Negi, "Guaranteeing secrecy using artificial noise," IEEE Trans. Wireless Commun., vol. 7, no. 6, pp. 2180–2189, June 2008.
- (2) S.-C. Lin and P.-H. Lin, "On ergodic secrecy capacity of multiple input wiretap channel with statistical CSIT," IEEE Trans. Inf. Forensics Security, vol. 8, no. 2, pp. 414–419, Feb. 2013.
- (3) P.-H. Lin, S.-H. Lai, S.-C. Lin, and H.-J. Su, "On optimal artificial-noise assisted secure beamforming for the fading eavesdropper channel," IEEE J. Select. Areas Commun., vol. 31, no. 9, pp. 1728–1740, Sept. 2013.

Tradeoff Energy Secrecy

- **Secrecy-energy trade-off** in single-antenna, single-carrier Gaussian wiretap channels is studied in terms of actual communication rate and consumed energy.
- **Information-theoretic analysis** of secret communications per transmission cost.
- Ratio between the **secrecy outage rate** and the **consumed power** analyzed for multiple-antenna systems.

- (1) C. Comaniciu and H. Poor, "On Energy-Secrecy Trade-Offs for Gaussian Wiretap Channels," IEEE Transactions on Information Forensics and Security, vol. 8, no. 2, pp. 314–323, Feb 2013.
- (2) M. El-Halabi, T. Liu, and C. N. Georghiadis, "Secrecy capacity per unit cost," IEEE Journal on Selected Areas in Communications, vol. 31, no. 9, pp. 1909–1920, September 2013.
- (3) X. Chen and L. Lei, "Energy-efficient optimization for physical layer security in multi-antenna downlink networks with QoS guarantee," IEEE Com. Lett., vol. 17, no. 4, pp. 637–640, Ap 2013.
- (4) X. Chen, C. Zhonga, C. Yuen, and H.-H. Chen, "Multi-antenna relayaided wireless physical layer security," IEEE Commun. Mag., vol. 53, no. 12, pp. 40–46, Dec. 2015.

Secure Energy Efficiency

Contribution

- With **statistical CSIT** (Gaussian spatially white distribution) to Eve and perfect CSIT to Bob, **SEE maximization problem**, with using of AN.
- Fractional, non-convex problem, tackled by **combination of fractional programming and sequential optimization** theory.
- Extensions: both channels statistically known or Eve channel is spatially correlated.
- **Complexity** analysis of the SEE problem.
Is the higher complexity of AN worth it?

Channel Model

$$\mathbf{y}_b = \mathbf{h}^H \mathbf{x} + \mathbf{z}_b,$$
$$\mathbf{y}_e = \mathbf{g}^H \mathbf{x} + \mathbf{z}_e,$$

- MISO channels with AWGN
- AN is used $\mathbf{x} = \mathbf{u} + \mathbf{v}$
- Resulting transmit covariance matrices

$$\mathbf{Q} = \mathbf{Q}_U + \mathbf{Q}_V$$

Problem Statement

$$\begin{aligned} \max \quad & \frac{R_S(\mathbf{Q}_U, \mathbf{Q}_V)}{\mu \text{tr}(\mathbf{Q}_U + \mathbf{Q}_V) + P_c} \\ \text{s.t.} \quad & \text{tr}(\mathbf{Q}_U + \mathbf{Q}_V) \leq P_{max} \\ & \mathbf{Q}_U \succeq \mathbf{0}, \mathbf{Q}_V \succeq \mathbf{0} \end{aligned}$$

- The objective is a fractional function, and therefore we will resort to **fractional programming theory**.
- Standard fractional programming does not work because **numerator is not concave**.

SEE maximization with uncorrelated \mathbf{g}

$$\max \frac{\left(\log \left(1 + \frac{\mathbf{h}^H \mathbf{Q}_U \mathbf{h}}{1 + \mathbf{h}^H \mathbf{Q}_V \mathbf{h}} \right) - \mathbb{E}_{\mathbf{g}} \left[\log \left(1 + \frac{\mathbf{g}^H \mathbf{Q}_U \mathbf{g}}{1 + \mathbf{g}^H \mathbf{Q}_V \mathbf{g}} \right) \right] \right)^+}{\mu \text{tr}(\mathbf{Q}_U + \mathbf{Q}_V) + P_c}$$

s.t. $\text{tr}(\mathbf{Q}_U + \mathbf{Q}_V) \leq P_{max}$
 $\mathbf{Q}_U \succeq \mathbf{0}, \mathbf{Q}_V \succeq \mathbf{0}$

- **Characterization of optimal directions** (eigenvectors) of both transmit covariance matrices.
- The remaining programming problem is easier but still with non-concave numerator. Thus we use **sequential optimization**.

Sequential Programming

- Instead of solving the difficult master problem, solve a **sequence of easier problems**.
- Consider a problem \mathbf{P} with objective f and a sequence of approximate problems \mathbf{P}_l with objectives f_l such that the following properties hold

$$\text{(P1)} \quad f_l(\mathbf{x}) \leq f(\mathbf{x}), \text{ for all } \mathbf{x};$$

$$\text{(P2)} \quad f_l(\mathbf{x}^{(\ell-1)}) = f(\mathbf{x}), \text{ with } \mathbf{x}^{(\ell-1)} \text{ the maximizer of } f_{l-1};$$

$$\text{(P3)} \quad \nabla f_l(\mathbf{x}^{(\ell-1)}) = \nabla f(\mathbf{x}).$$

- Then solving the sequence of problems, the value will **converge and if the optimization variables converges, too, then to a point fulfilling the KKT conditions**.

Technical Details

$$\max_{(P_U, P_{V_s}, P_{V_r})} \frac{\log\left(1 + \frac{\|h\|^2 P_U}{1 + \|h\|^2 P_{V_s}}\right) - \mathbb{E}\left[\log\left(1 + \frac{\tilde{G}_1 P_U}{1 + \tilde{G}_1 P_{V_s} + \left(\sum_{i=2}^{n_T} \tilde{G}_i\right) P_{V_r}}\right)\right]}{\mu(P_U + P_{V_s} + (n_T - 1)P_{V_r}) + P_c}$$

s.t. $P_U + P_{V_s} + (n_T - 1)P_{V_r} \leq P_{max}$
 $P_{V_s} \geq 0, P_{V_r} \geq 0, P_U \geq 0.$

$$\underbrace{\log(1 + \|h\|^2(P_U + P_{V_s})) + \mathbb{E}_{\mathbf{G}}\left[\log\left(1 + \tilde{G}_1 P_{V_s} + \tilde{G}_t P_{V_r}\right)\right]}_{f^+(P_U, P_{V_s}, P_{V_r})} -$$

$$\underbrace{\left\{\log(1 + \|h\|^2 P_{V_s}) + \mathbb{E}_{\mathbf{G}}\left[\log\left(1 + \tilde{G}_1(P_U + P_{V_s}) + \tilde{G}_t P_{V_r}\right)\right]\right\}}_{f^-(P_U, P_{V_s}, P_{V_r})},$$

Iterative Algorithm

Algorithm 1 SEE maximization with uncorrelated g .

$\ell = 0; \epsilon > 0$; Select a feasible $P_0^{(\ell)}$;
while $\left| \text{SEE} \left(P_0^{(\ell)} \right) - \text{SEE} \left(P_0^{(\ell-1)} \right) \right| > \epsilon$ **do**
 Solve Problem (21) by fractional programming theory
 (see Appendix A) and set P as the solution.
 $P_0^{(\ell)} = P$;
 $\ell = \ell + 1$;
end while

$$\max_{P_U, P_{V_s}, P_{V_r}} \frac{f^+(P_U, P_{V_s}, P_{V_r}) - f^-(P_{U,0}, P_{V_s,0}, P_{V_r,0}) - \frac{\partial f^-}{\partial P_U} |_{P_0} (P_U - P_{U,0}) - \frac{\partial f^-}{\partial P_{V_s}} |_{P_0} (P_{V_s} - P_{V_s,0}) - \frac{\partial f^-}{\partial P_{V_r}} |_{P_0} (P_{V_r} - P_{V_r,0})}{\mu(P_U | P_{V_s} | (n_T - 1)P_{V_r}) | P_c} \quad (21a)$$

$$\text{s.t. } P_U + P_{V_s} + P_{V_r} \leq P_{max} \quad (21b)$$

$$P_U > 0, P_{V_s} > 0, P_{V_r} > 0 \quad (21c)$$

Iterative Algorithm

Algorithm 1 SEE maximization

$\ell = 0; \epsilon > 0; \text{Set } P_{U,0}, P_{V_s,0}, P_{V_r,0}$

while $|SEE(\ell) - SEE(\ell-1)| > \epsilon$

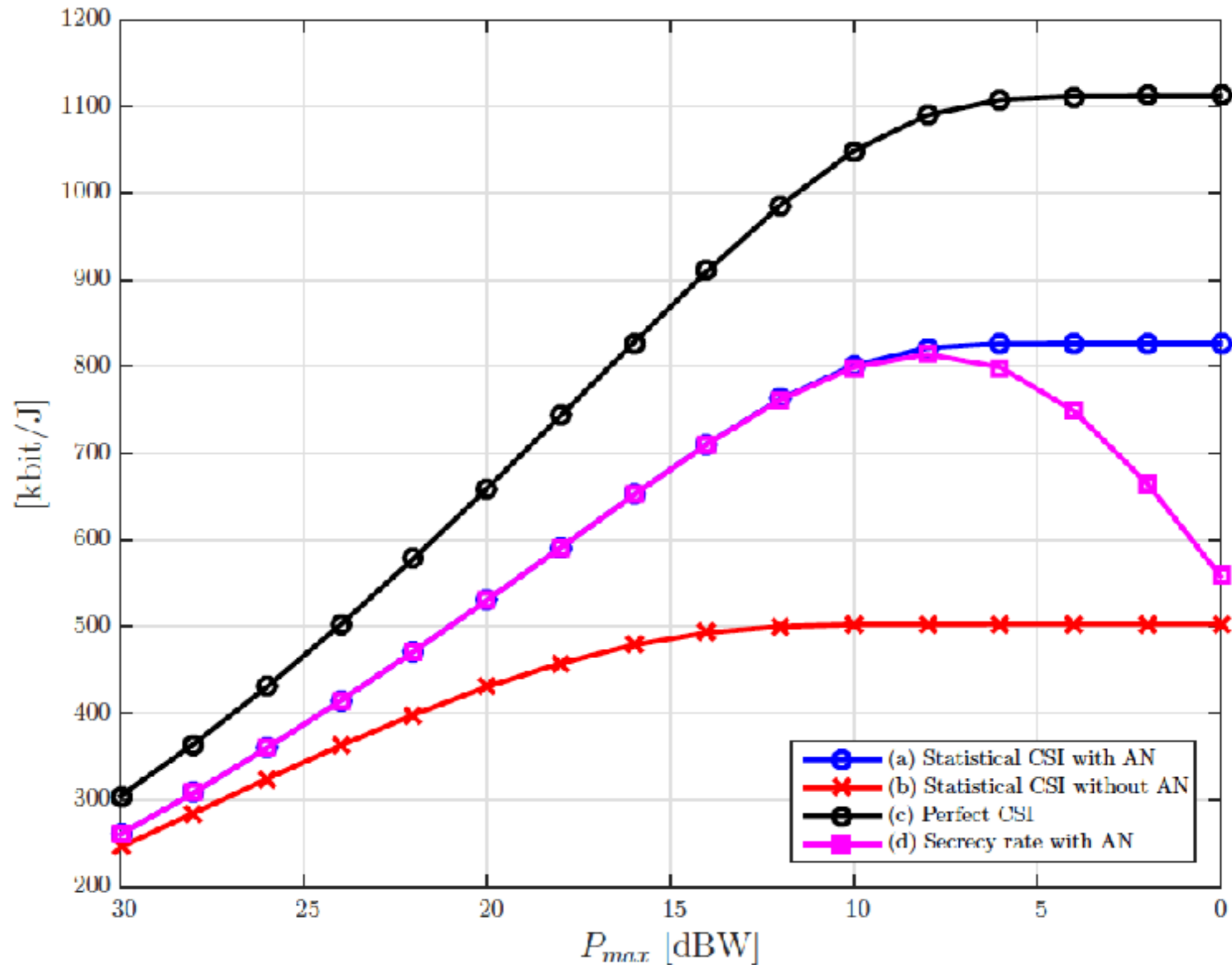
Proposition 1. After each iteration of Algorithm 1, the value of the true SEE in (10a) is not decreased. Moreover, Algorithm 1 is guaranteed to converge to a $P^* = (P_U^*, P_{V_s}^*, P_{V_r}^*)$ which fulfills the KKT optimality conditions of Problem (10).

$$\begin{aligned} \max_{P_U, P_{V_s}, P_{V_r}} & \frac{f^+(P_U, P_{V_s}, P_{V_r}) - f^-(P_{U,0}, P_{V_s,0}, P_{V_r,0}) - \frac{\partial f^-}{\partial P_U} |_{P_0} (P_U - P_{U,0}) - \frac{\partial f^-}{\partial P_{V_s}} |_{P_0} (P_{V_s} - P_{V_s,0}) - \frac{\partial f^-}{\partial P_{V_r}} |_{P_0} (P_{V_r} - P_{V_r,0})}{\mu(P_U | P_{V_s} | (n_T - 1)P_{V_r}) | P_c} & (21a) \\ \text{s.t. } & P_U + P_{V_s} + P_{V_r} \leq P_{max} & (21b) \\ & P_U > 0, P_{V_s} > 0, P_{V_r} > 0 & (21c) \end{aligned}$$

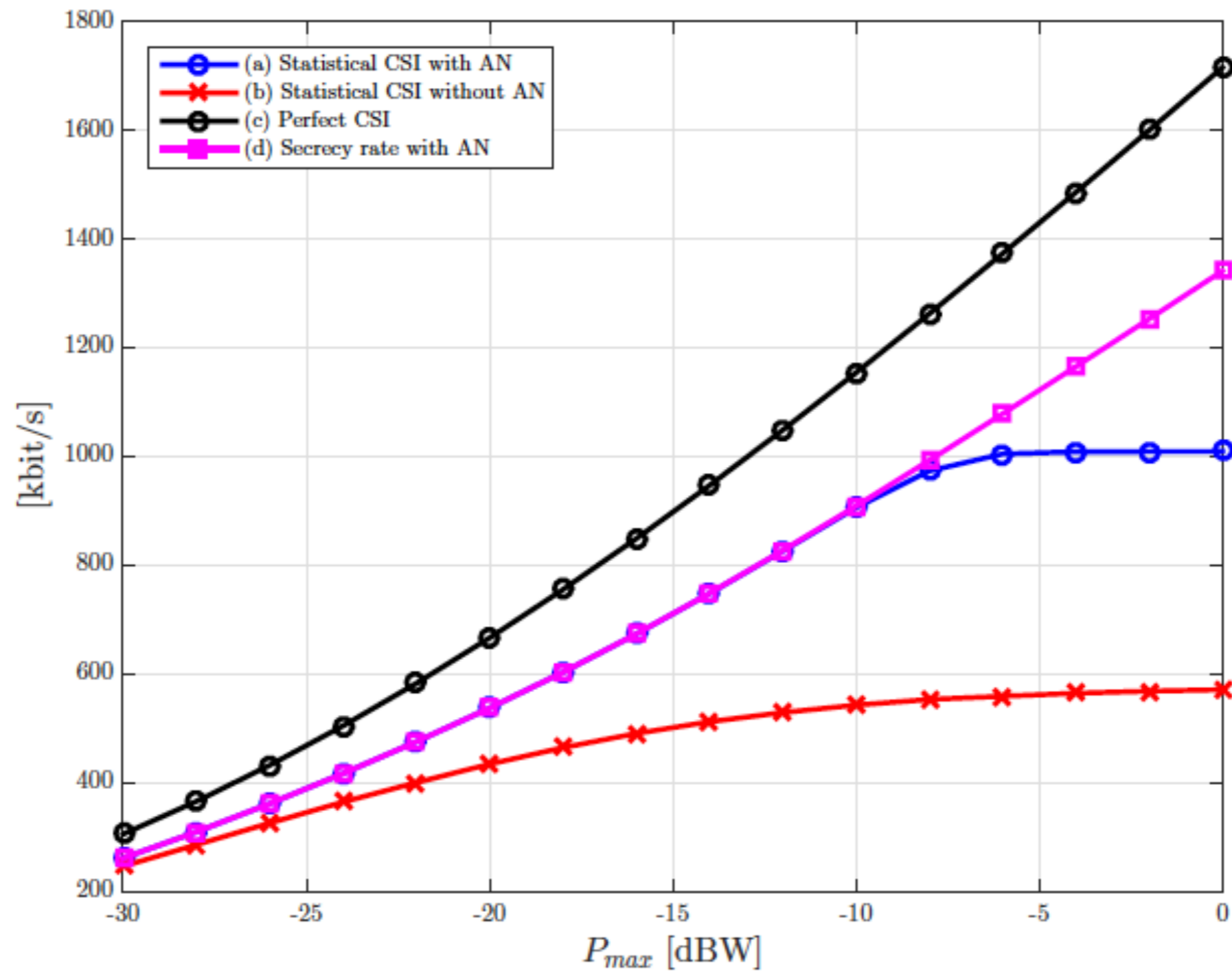
Numerical Setup

- Constant Power $P_c = 1$ W, efficiency $\mu = 1$
- Three antennas, uncorrelated channels \mathbf{h} and \mathbf{g}
- Path-loss model with decay factor 3.5 and distances randomly generated [100, 1000] m.
- Noise power is product of 10 dB receive noise figure, noise density -174 dBm/Hz and bandwidth $W = 180$ kHz (typical LTE values).
- Averaging over 1000 channel realizations.

Numerical Illustration



Numerical Illustration



Energy and Complexity

- Take timing and energy consumption into account

$$SEE = \frac{(T_c - T_{ra})R_S(Q_U, Q_V)}{(T_c - T_{ra})\mu\text{tr}(Q_U + Q_V) + T_c P_c + E_{ra}}$$

- Energy consumed during digital signal processing

$$E_{ra} = N_{op}\tau V_{dd}I$$

- Number of operations for executing the Algorithm

with AN $N_{op}^{AN} = \mathcal{O}(I_S^{AN}(I_D^{AN}\sqrt{m+1}(n^3 + mn^2 + mn)) + 4N_p)$

without AN $N_{op} = \mathcal{O}(I_D\sqrt{m+1}(n^3 + mn^2 + mn))$

Energy and Complexity

- Take timing and energy consumption into account

$$SEE = \frac{(T_c - T_{ra})R_S(Q_U + Q_V)}{(T_c - T_{ra})\mu \text{tr}(Q_U + Q_V) + T_c P_c + E_{ra}}$$

processor supply voltage

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Energy and Complexity

- Take timing and processor cycle time to account

$$SEE = \frac{(I_c - I_{ra})R_S(Q_U + Q_V)}{(T_c - T_{ra})\mu\text{tr}(Q_U + Q_V) - T_c P_c + E_{ra}}$$

processor cycle time

processor supply voltage

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Energy and Complexity

- Take timing and processor cycle time to account

$$SEE = \frac{(I_c - I_{ra})R_S(Q_U + Q_V)}{(T_c - T_{ra})\mu tr(Q_U + Q_V)}$$

processor cycle time

processor supply voltage

Current drawn by the processor during algorithm execution

- Energy consumed during digital signal processing

$$E_{ra} = N_{op}\tau V_{dd}I$$

- Number of operations for executing the Algorithm

with AN $N_{op}^{AN} = \mathcal{O}(I_S^{AN}(I_D^{AN}\sqrt{m+1}(n^3 + mn^2 + mn)) + 4N_p)$

without AN $N_{op} = \mathcal{O}(I_D\sqrt{m+1}(n^3 + mn^2 + mn))$

Energy and Complexity

- Take timing and processor cycle time into account

SEE = $\frac{(I_c - I_{ra})R_S(Q_U + Q_V)}{Q_U + Q_V}$

processor cycle time

processor supply voltage

Number of flops required to execute the algorithm

Current drawn by the processor during algorithm execution

Energy consumed during digital signal processing

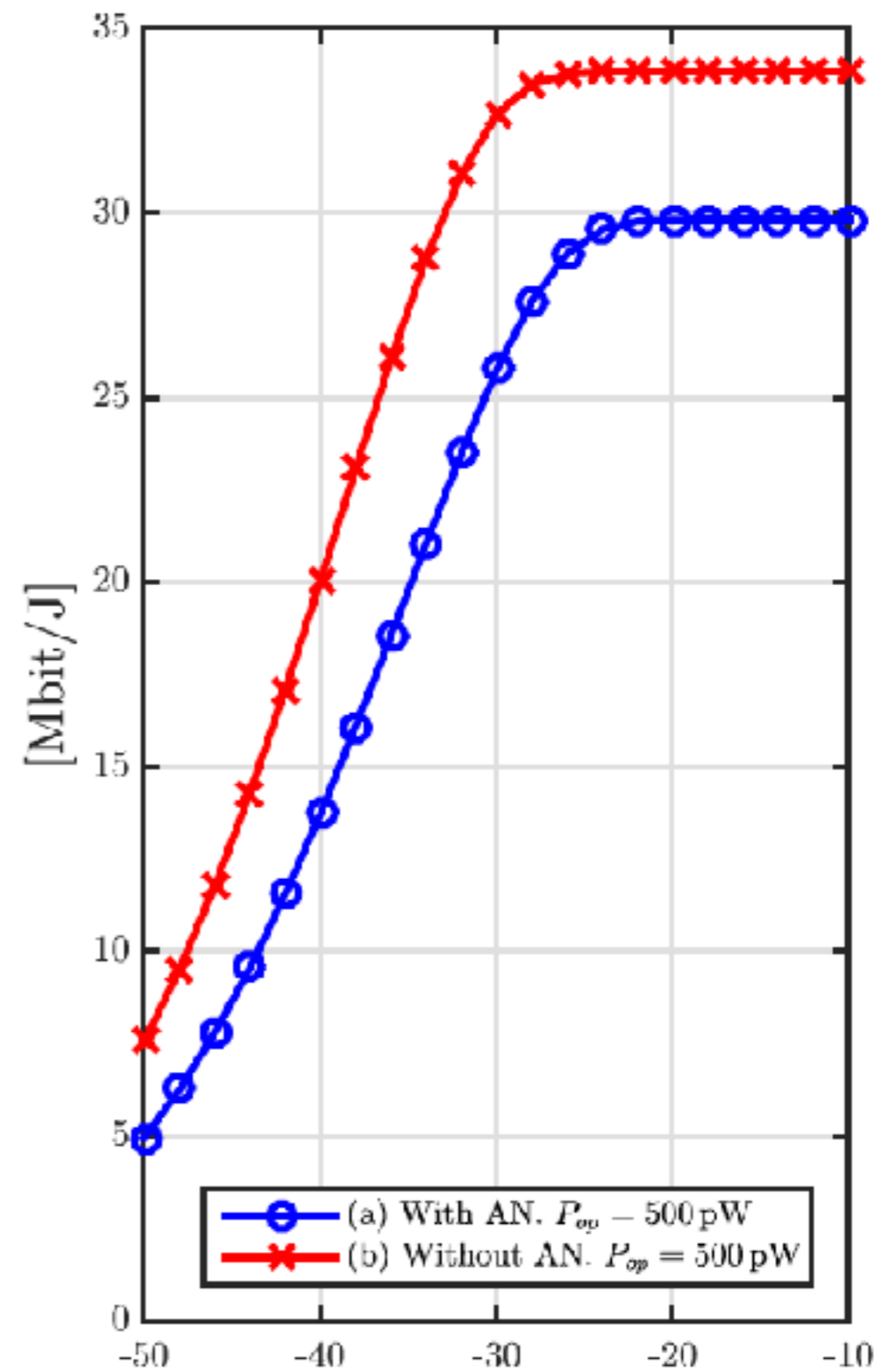
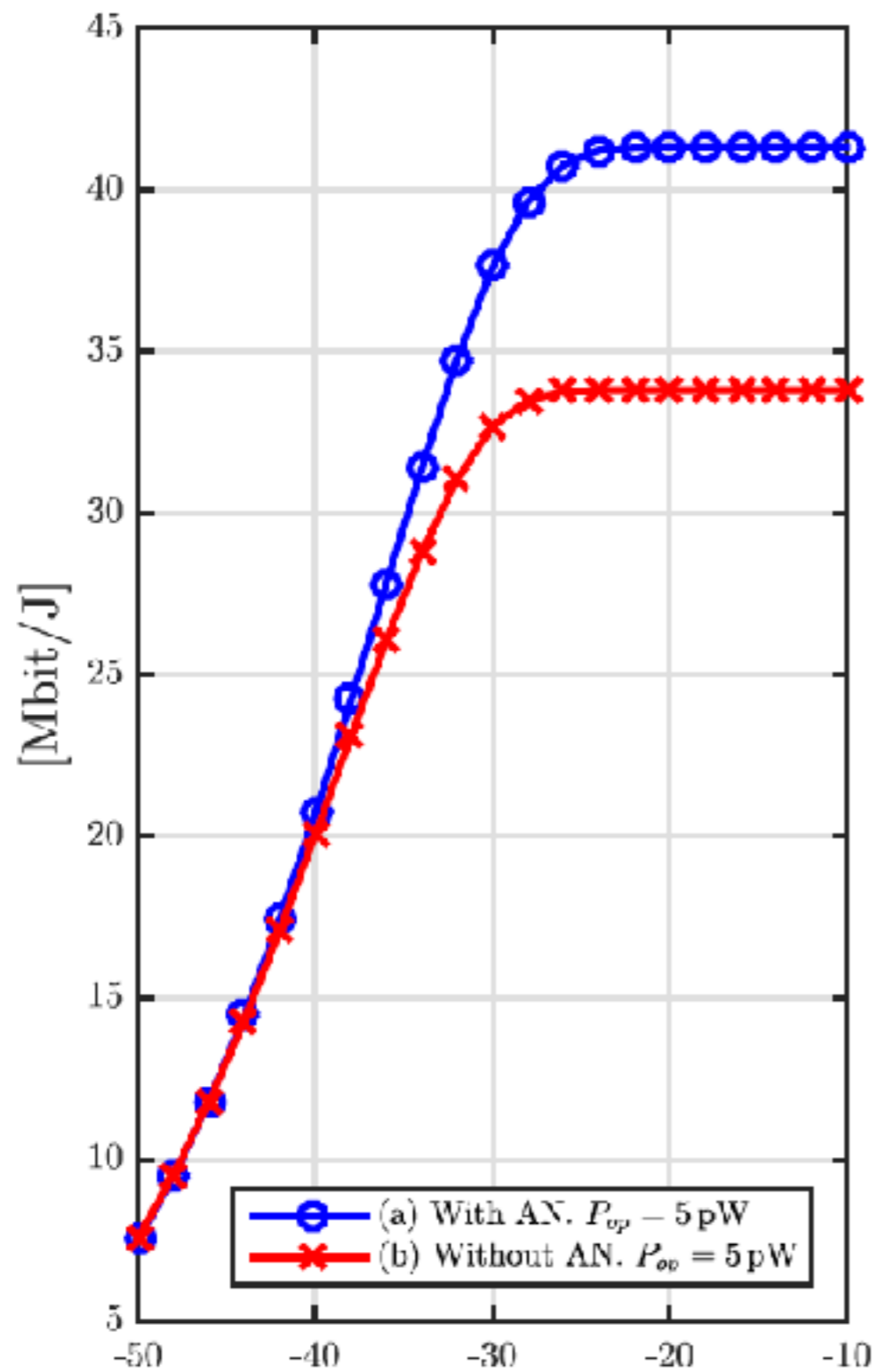
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without AN $N_{op} = \mathcal{O}(I_D \sqrt{m+1}(n^3 + mn^2 + mn))$

Is AN worth it?



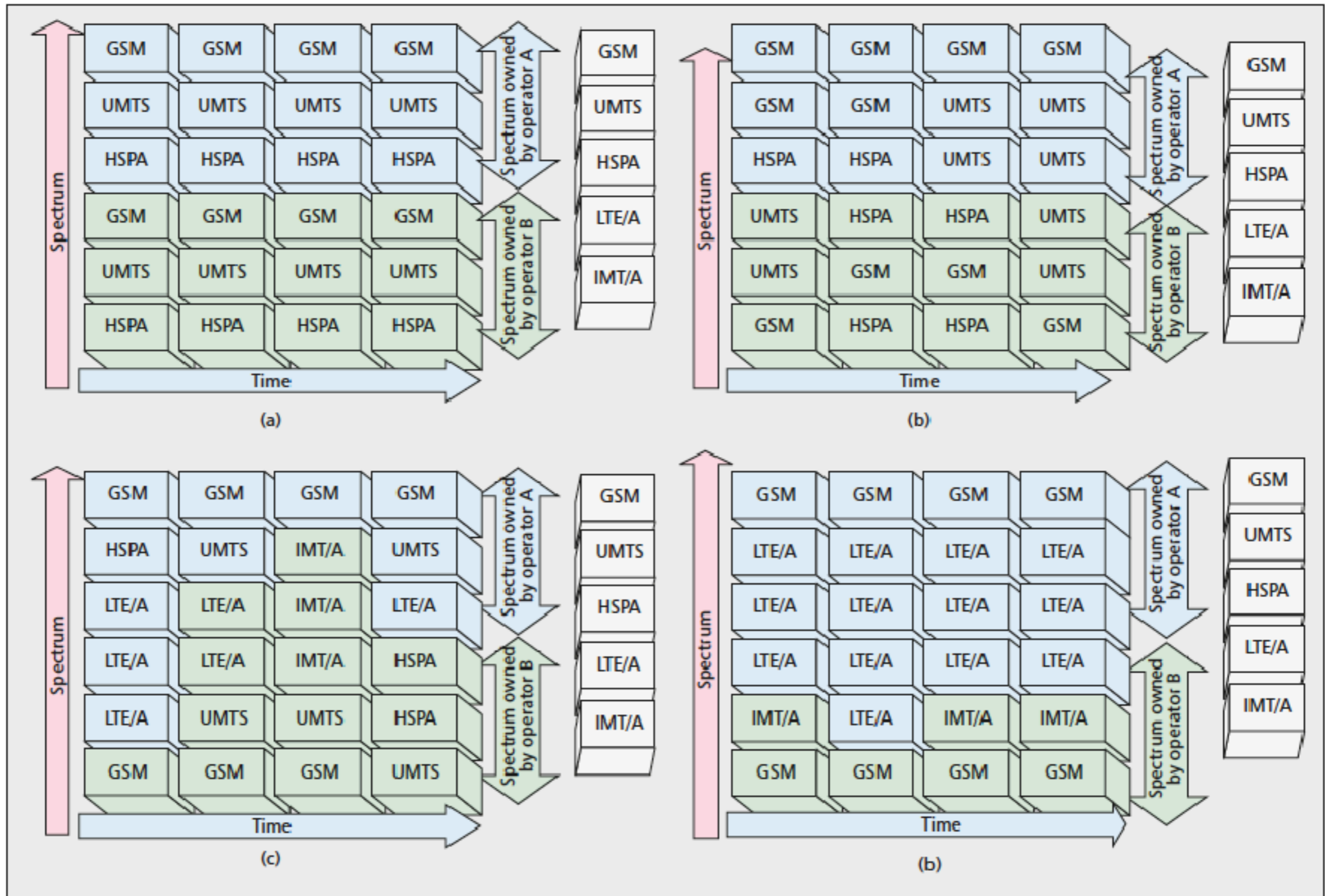
Conclusions

SEE Optimization

- Programming problems for **secrecy rate maximization** for **different types of CSIT with AN**.
- Combination of **fractional programming** with **sequential programming** results in local optimum.
- **Gain of AN depends** on the implementation of iterative algorithm and the **energy consumption per operation**.

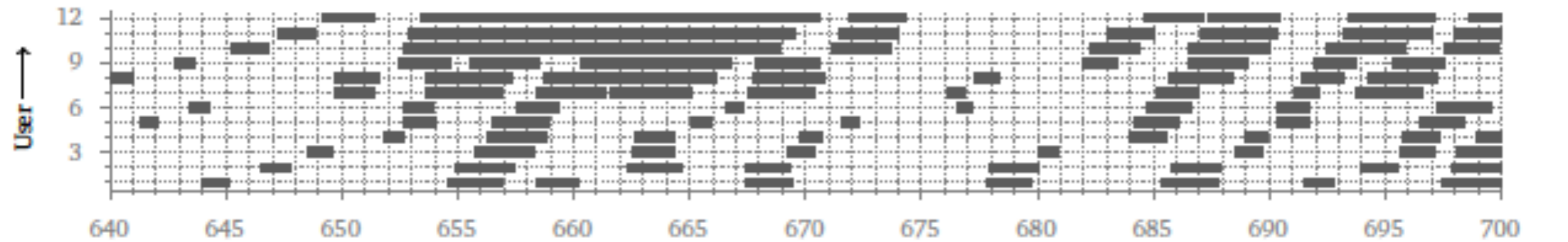
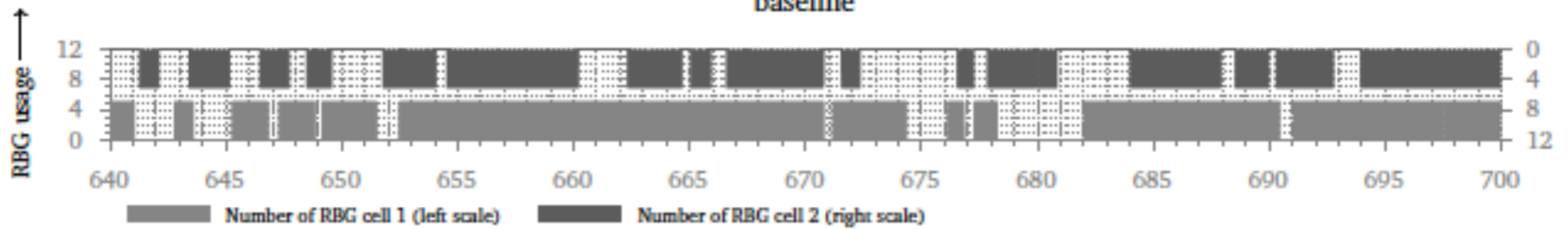
From Spectrum Sharing to Service Trading

Spectrum Sharing Revisited

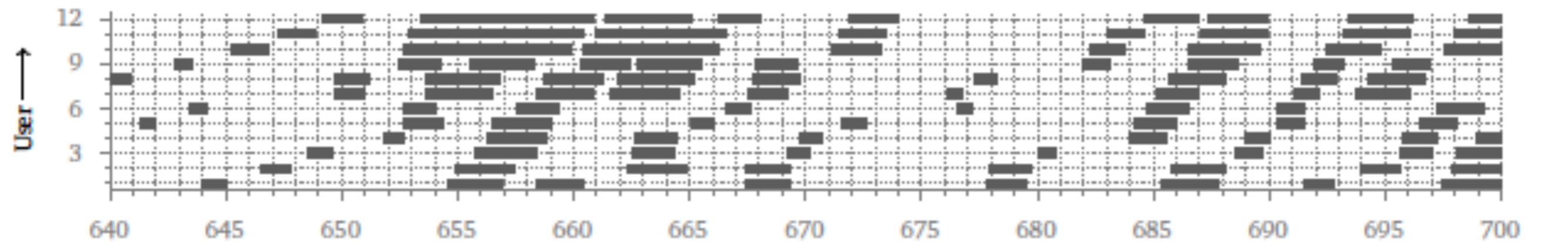
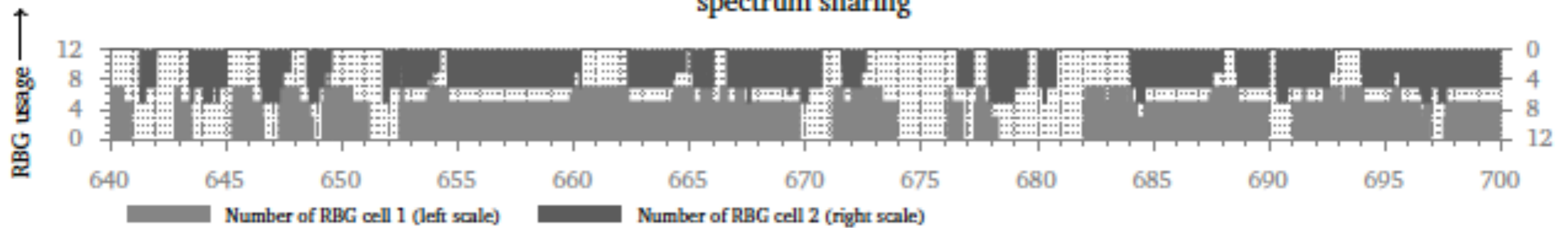


E. Jorswieck, L. Badia, T. Fahldieck, E. Karipidis and J. Luo,
 "Spectrum sharing improves the network efficiency for cellular operators,"
 in **IEEE Communications Magazine**, vol. 52, no. 3, pp. 129-136, March 2014.

baseline

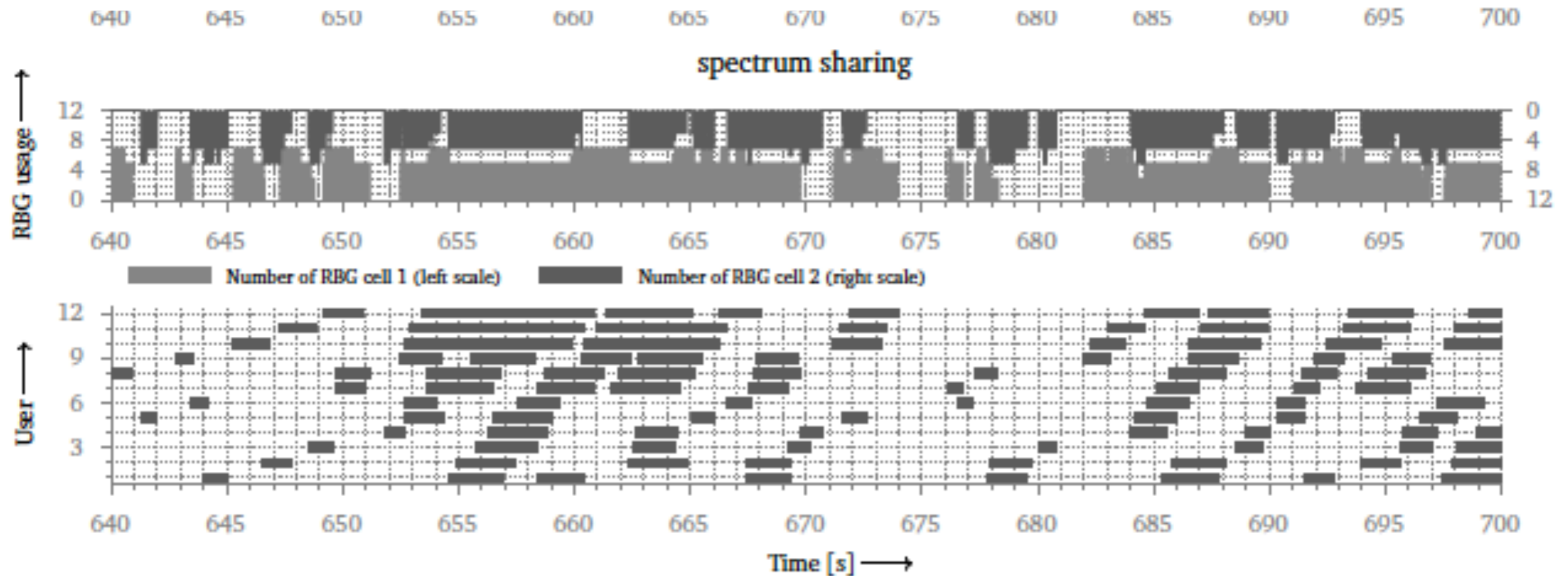


spectrum sharing

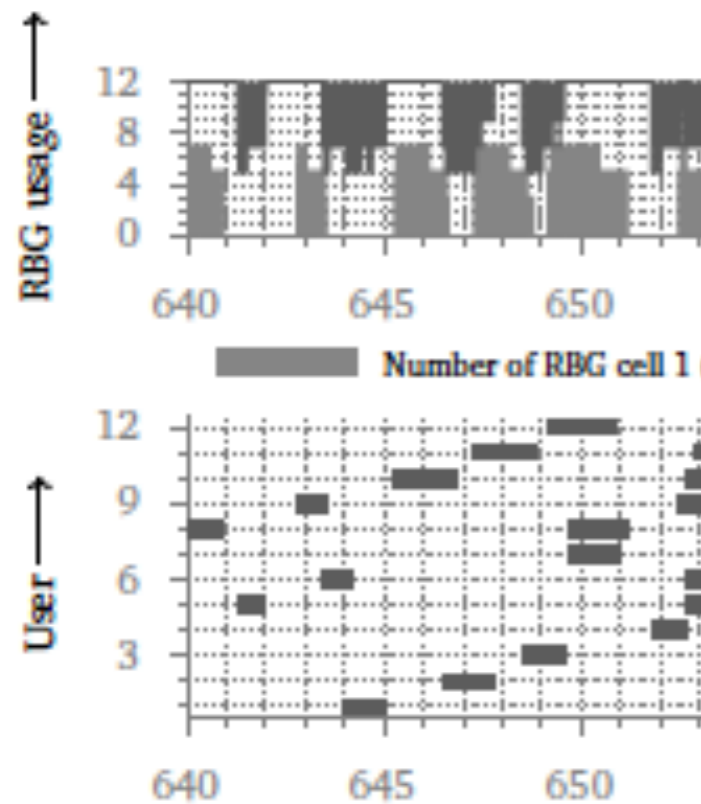


Time [s] →

Scenario	95 %ile		Average		
	Absolute	Gain	Absolute	Gain	
high, equal load	0.684 → 1.327 Mbps	94.0 %	1.802 → 3.361 Mbps	86.5 %	
high, unequal load	0.473 → 1.345 Mbps	184.4 %	1.511 → 3.373 Mbps	123.2 %	
low, equal load	1.171 → 2.302 Mbps	96.6 %	2.427 → 4.427 Mbps	82.4 %	
low, unequal load	0.917 → 2.312 Mbps	152.1 %	2.229 → 4.470 Mbps	100.5 %	



Scenario	95 %ile		Average		
	Absolute	Gain	Absolute	Gain	
high, equal load	0.684 → 1.327 Mbps	94.0 %	1.802 → 3.361 Mbps	86.5 %	
high, unequal load	0.473 → 1.345 Mbps	184.4 %	1.511 → 3.373 Mbps	123.2 %	
low, equal load	1.171 → 2.302 Mbps	96.6 %	2.427 → 4.427 Mbps	82.4 %	
low, unequal load	0.917 → 2.312 Mbps	152.1 %	2.229 → 4.470 Mbps	100.5 %	

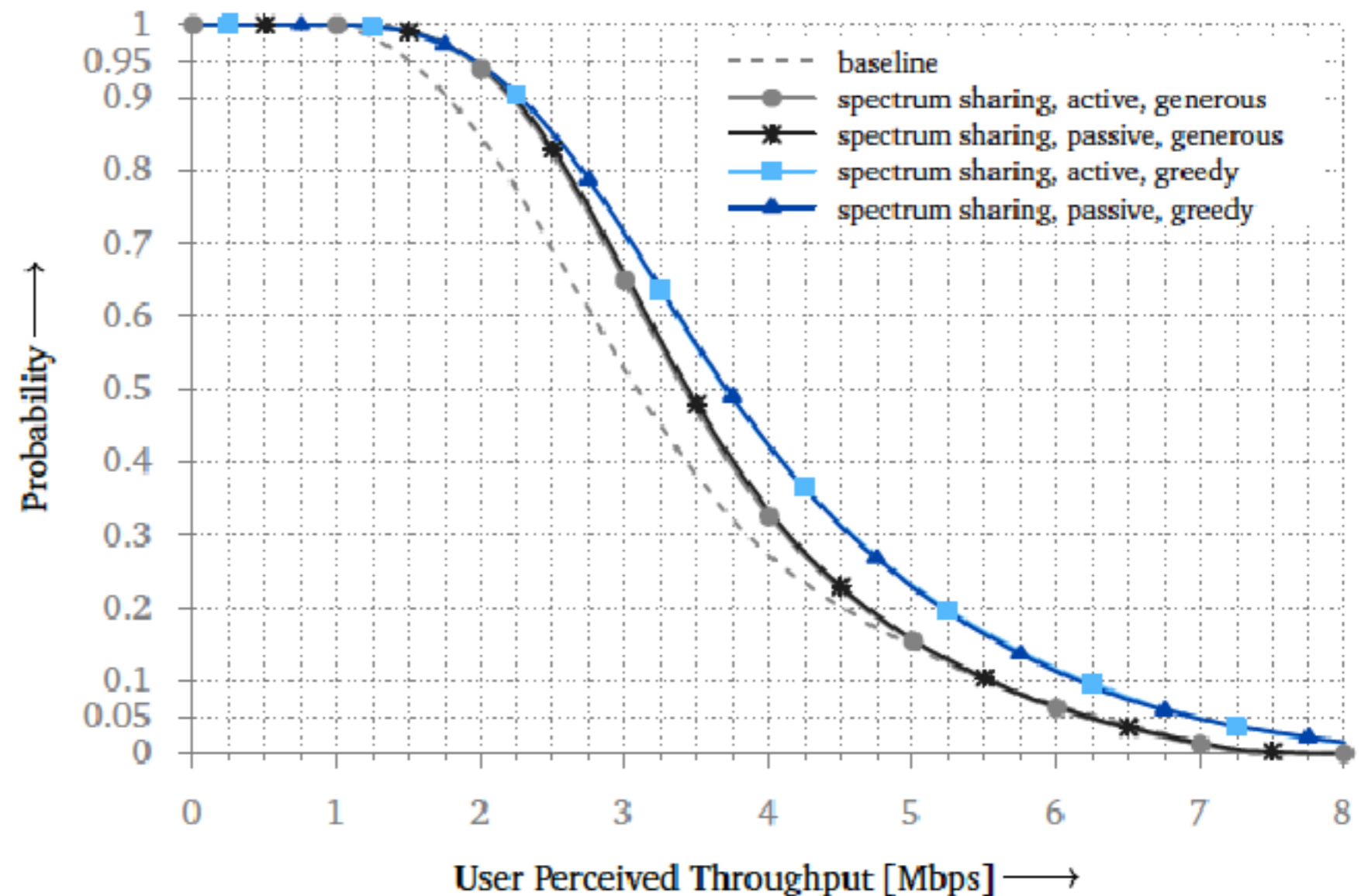


Scenario	Average Latency		Average Invalid Flows	
	Absolute	Gain	Absolute	Gain
high, equal load	1546.9 → 822.1 ms	88.2 %	114.1 → 61.2	86.4 %
high, unequal load	2239.2 → 821.7 ms	172.5 %	214.6 → 59.5	260.7 %
low, equal load	1020.4 → 565.9 ms	80.3 %	53.8 → 30.1	78.7 %
low, unequal load	1164.7 → 564.8 ms	106.2 %	52.2 → 30.4	71.7 %

System Level Results

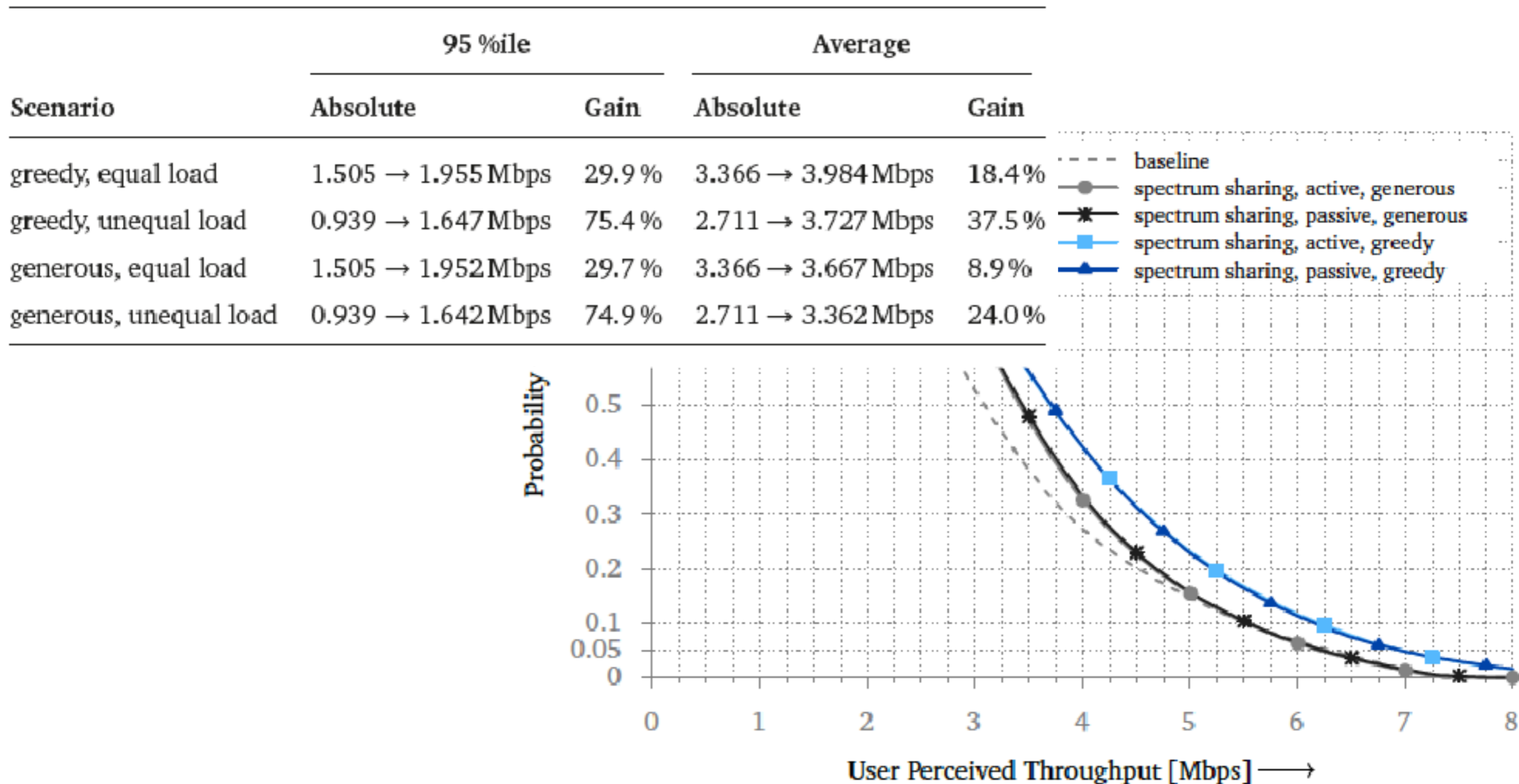
Table 5.5 – Number of trades.

Scenario	Fast negotiator	Slow negotiator
greedy, equal load	39951	4130
greedy, unequal load	50454	5096
generous, equal load	24326	2658
generous, unequal load	33643	3467



System Level Results

Table 5.6 – Summary of user throughput (UPT) gains.



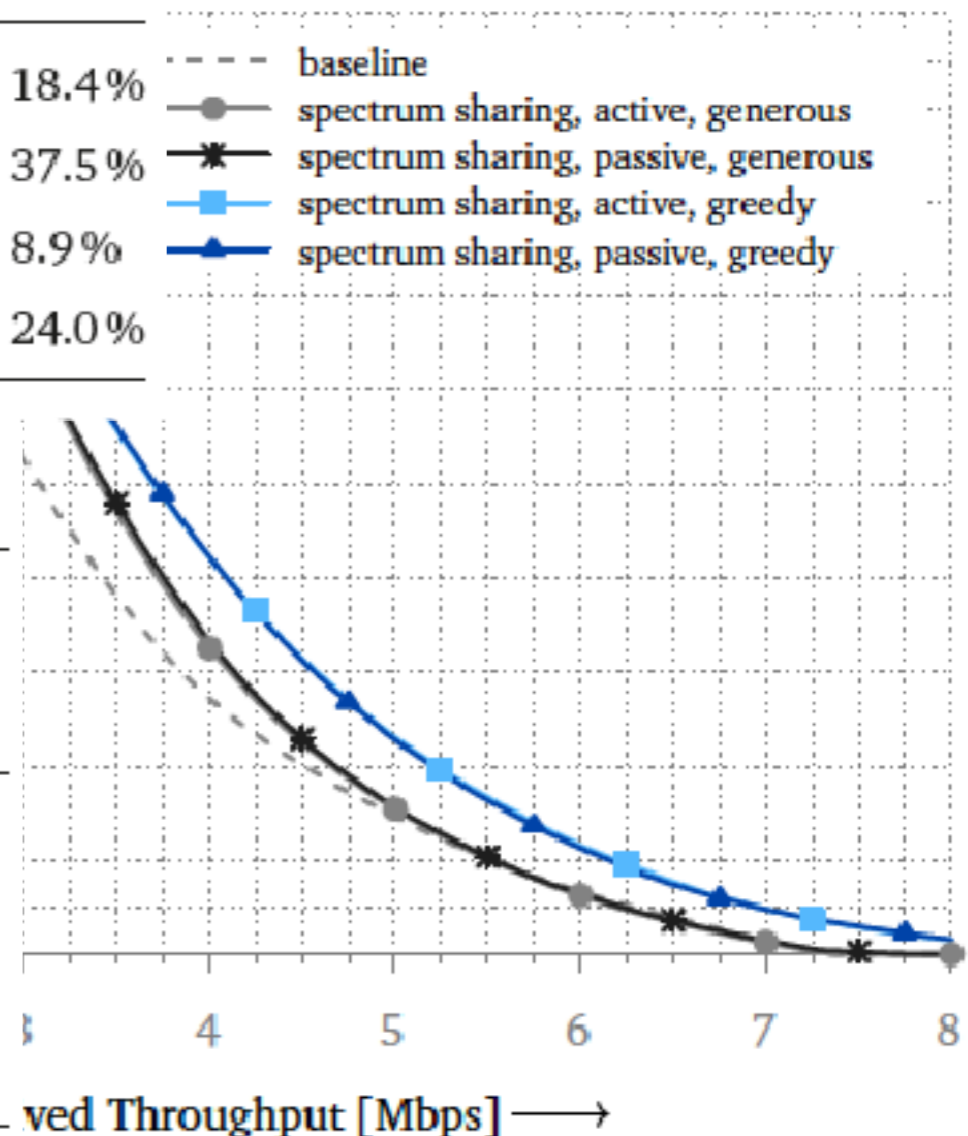
System Level Results

Table 5.6 – Summary of user throughput (UPT) gains.

Scenario	95 %ile		Average	
	Absolute	Gain	Absolute	Gain
greedy, equal load	1.505 → 1.955 Mbps	29.9 %	3.366 → 3.984 Mbps	18.4 %
greedy, unequal load	0.939 → 1.647 Mbps	75.4 %	2.711 → 3.727 Mbps	37.5 %
generous, equal load	1.505 → 1.952 Mbps	29.7 %	3.366 → 3.667 Mbps	8.9 %
generous, unequal load	0.939 → 1.642 Mbps	74.9 %	2.711 → 3.362 Mbps	24.0 %

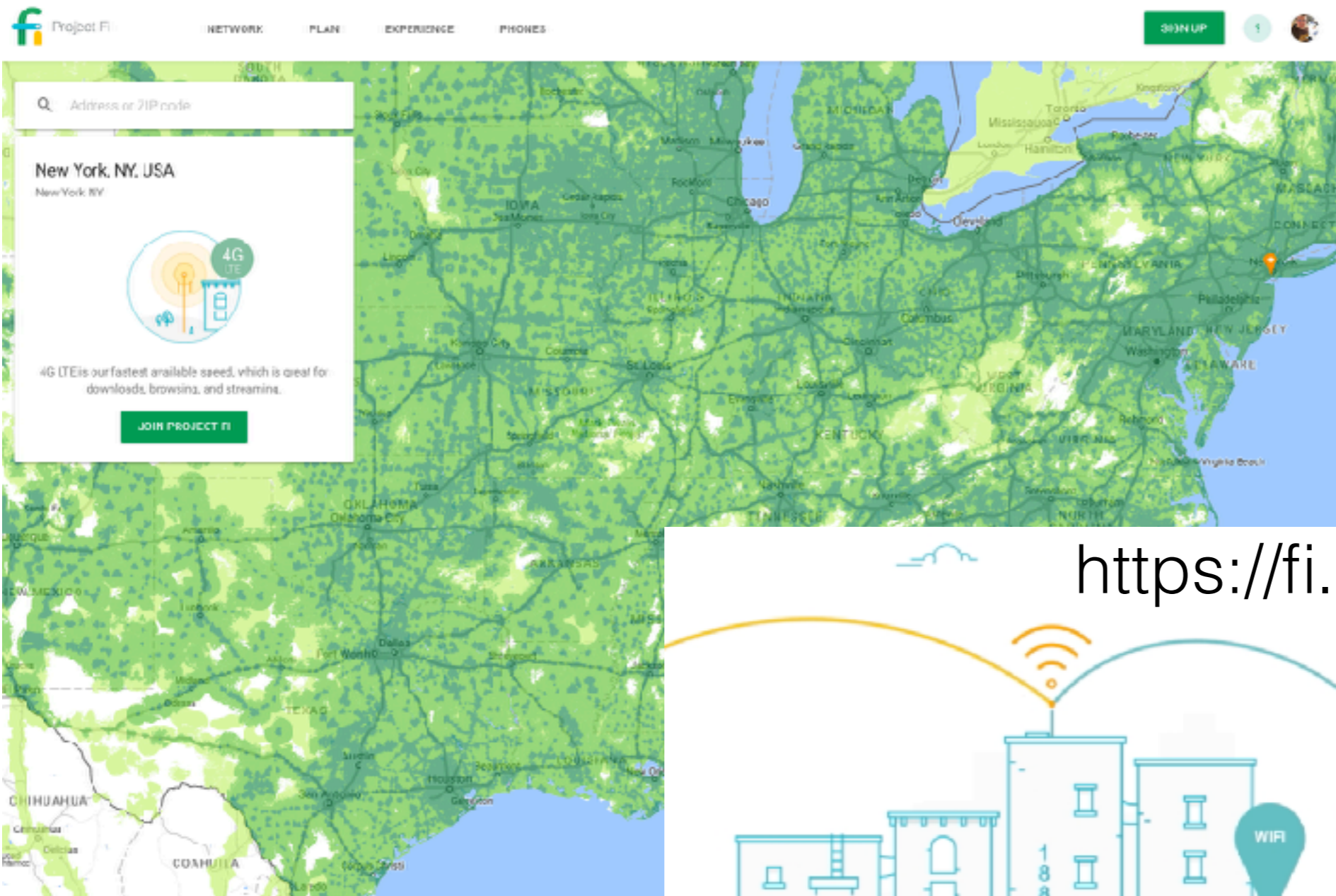
Table 5.7 – Summary of QoS aspects.

Scenario	Average Latency		Average Invalid Flows	
	Absolute	Gain	Absolute	Gain
greedy, equal load	770.7 → 629.0 ms	18.4 %	113.7 → 111.1	2.3 %
greedy, unequal load	1130.7 → 698.1 ms	38.3 %	115.9 → 111.0	4.2 %
generous, equal load	770.7 → 653.5 ms	15.2 %	113.7 → 111.9	1.6 %
generous, unequal load	1130.7 → 736.0 ms	34.9 %	115.9 → 111.6	3.7 %



The **tragedy of the commons** is an economic theory of a situation within a shared-resource system where individual users acting independently according to their own self-interest behave contrary to the common good of all users by depleting that resource through their collective action.

https://en.wikipedia.org/wiki/Tragedy_of_the_commons

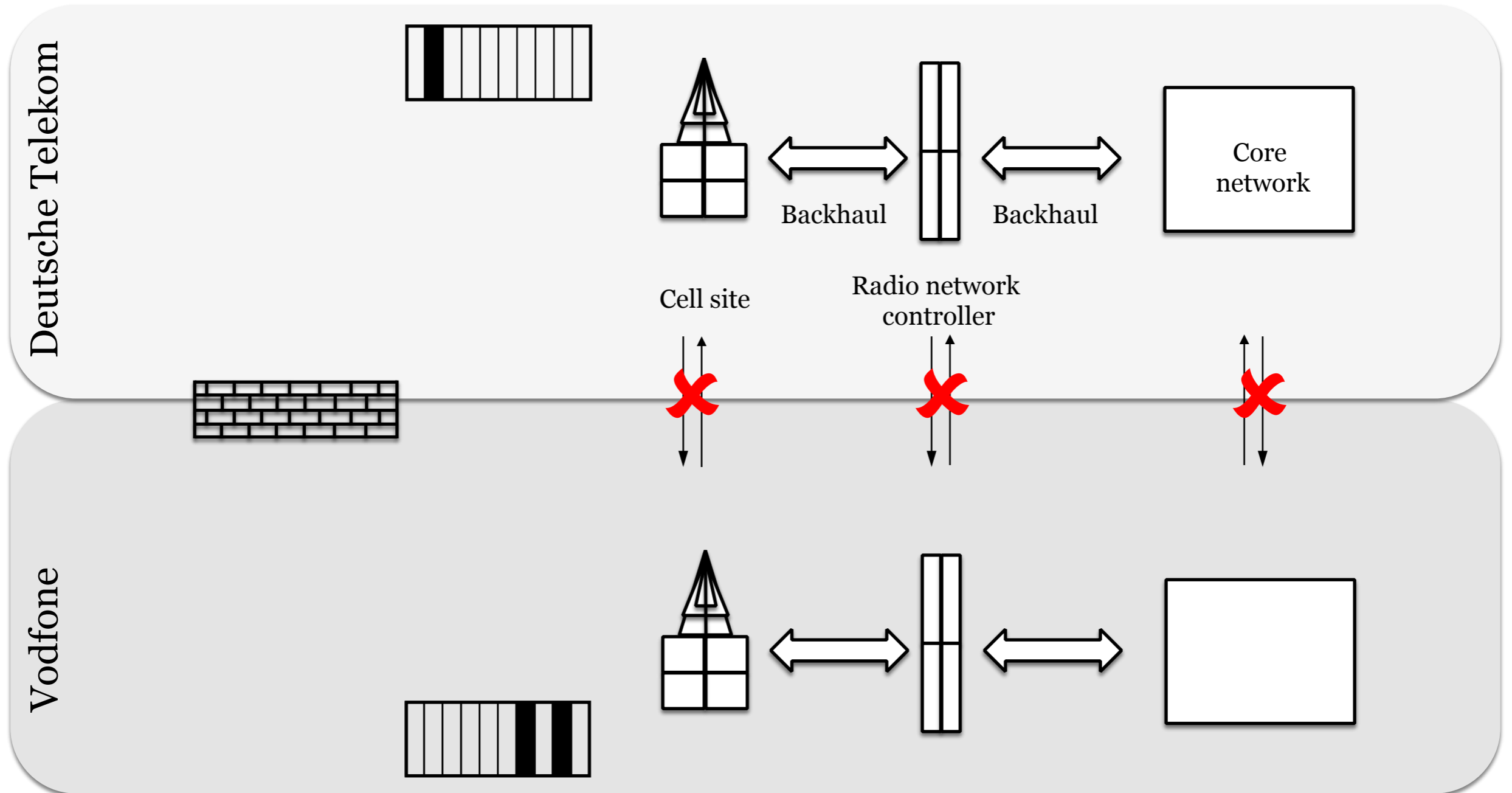


<https://fi.google.com/about/>

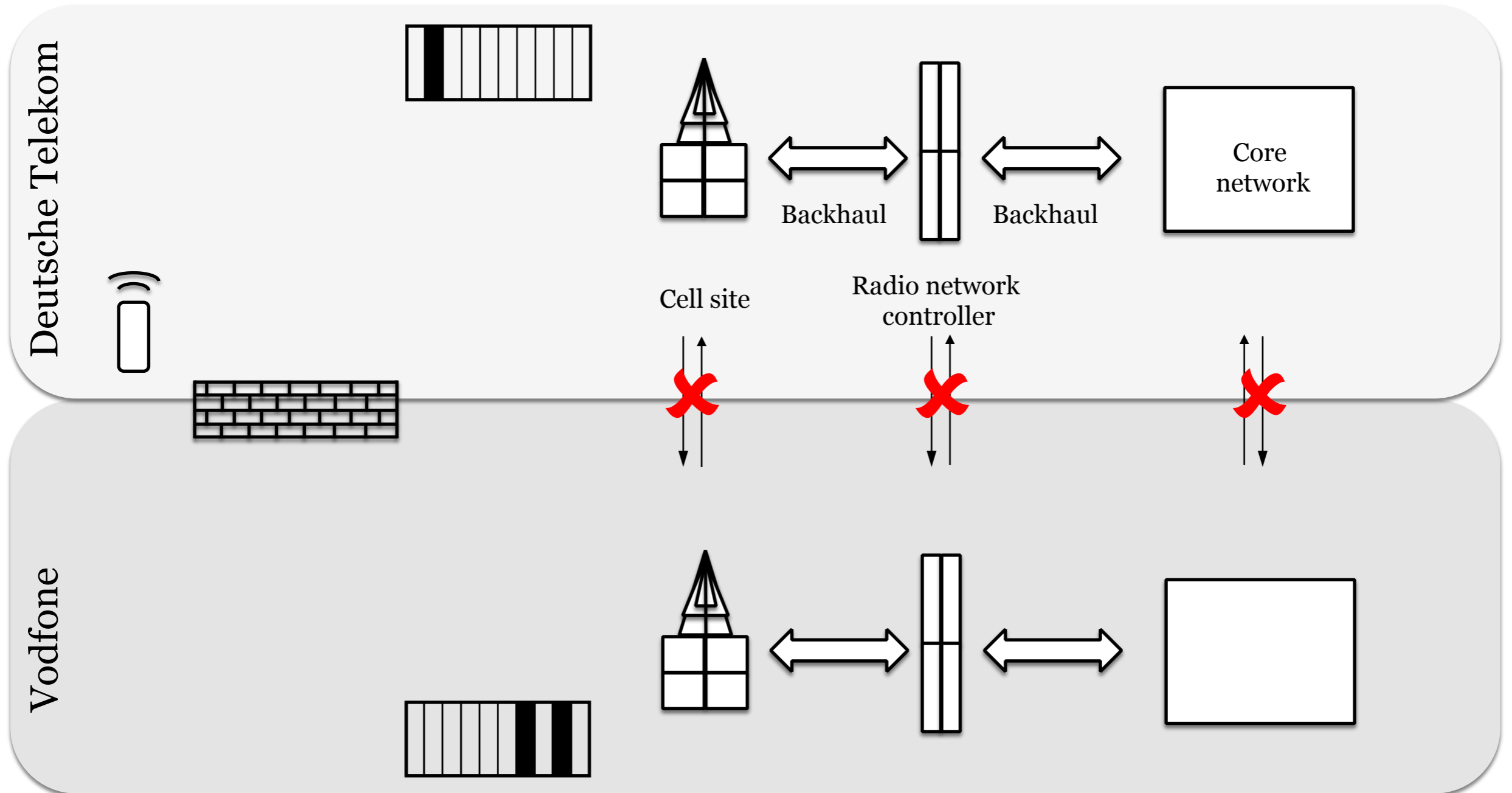


Google Project Fi

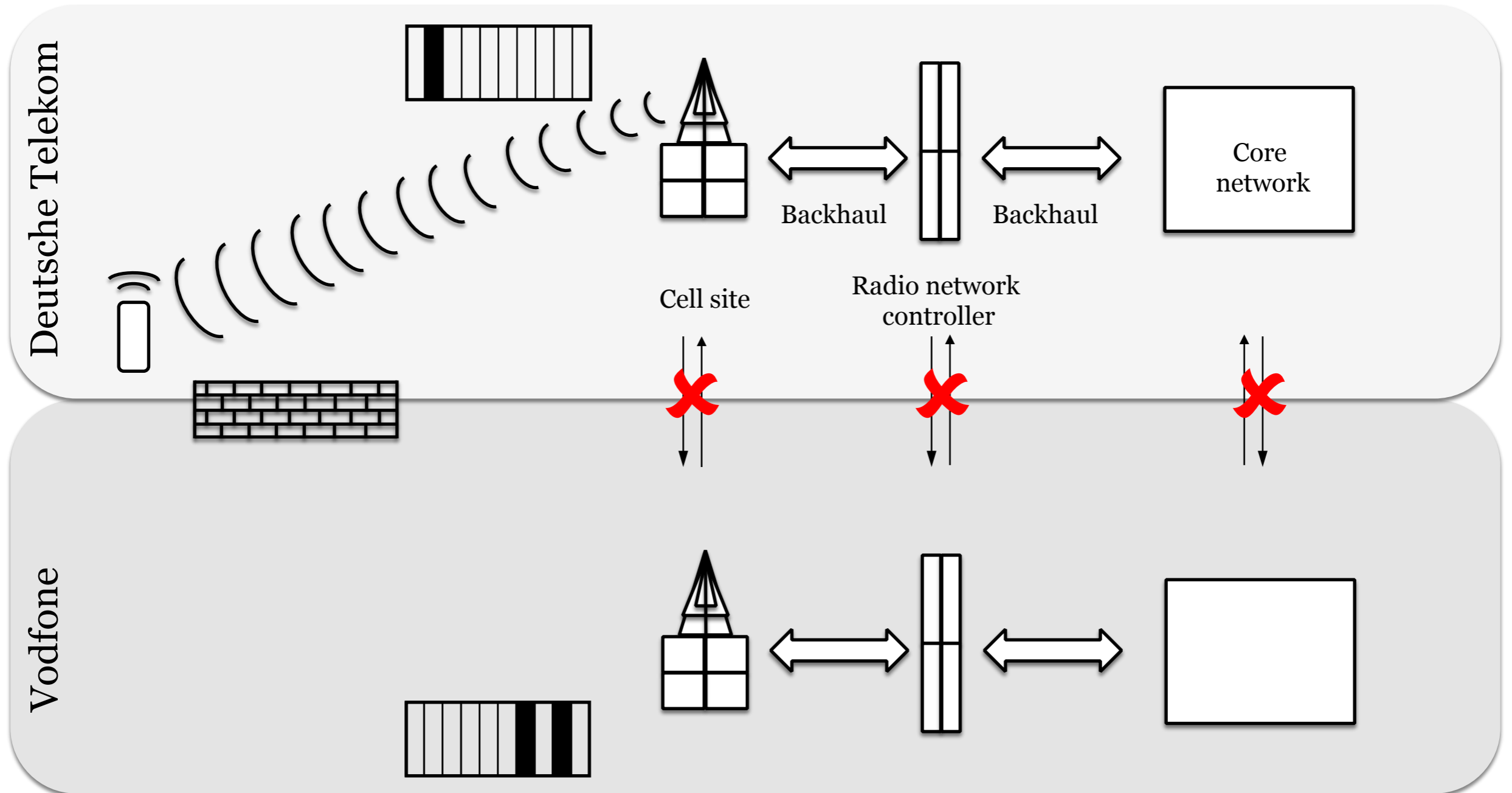
Service Trading



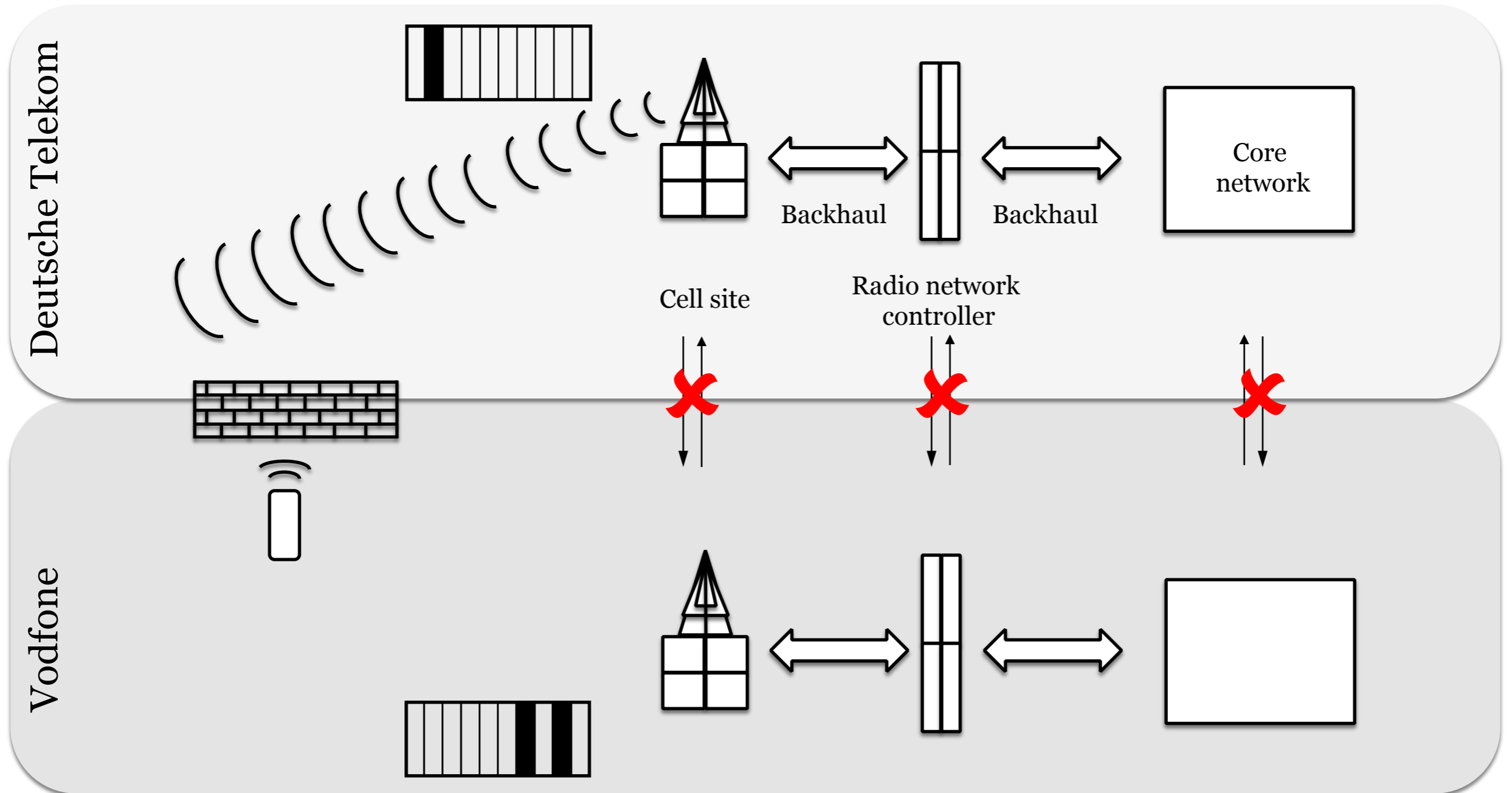
Service Trading



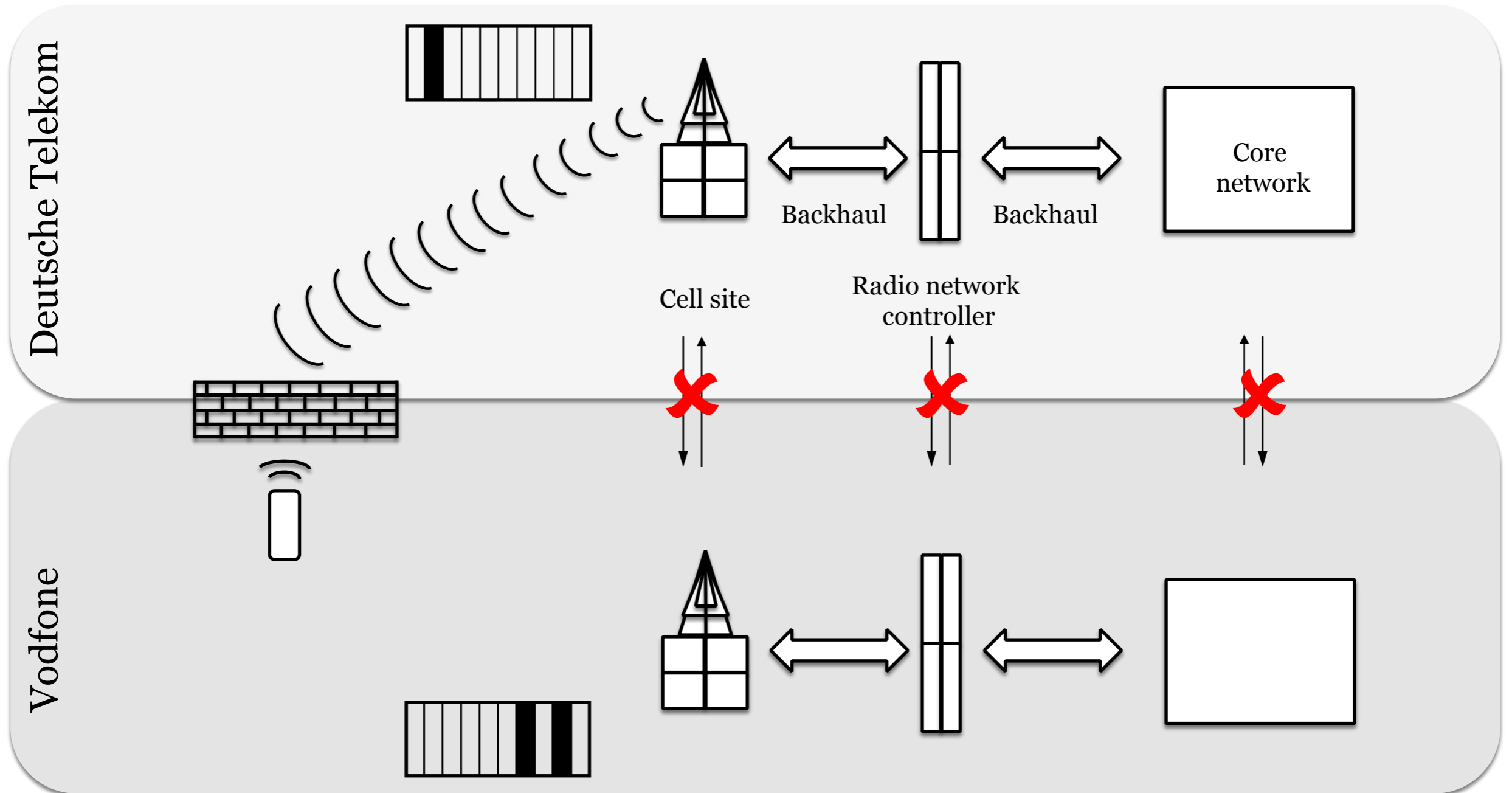
Service Trading



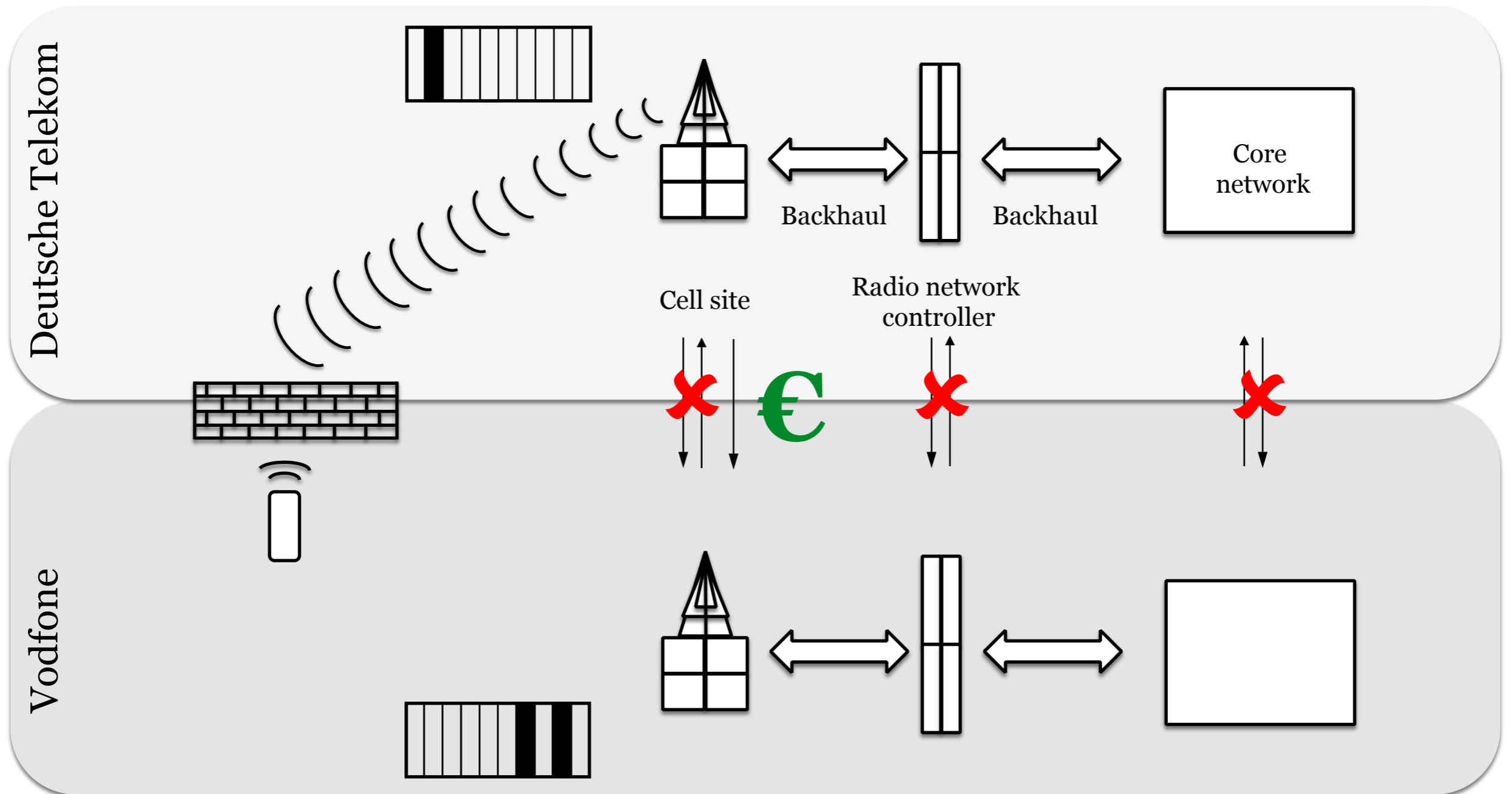
Service Trading



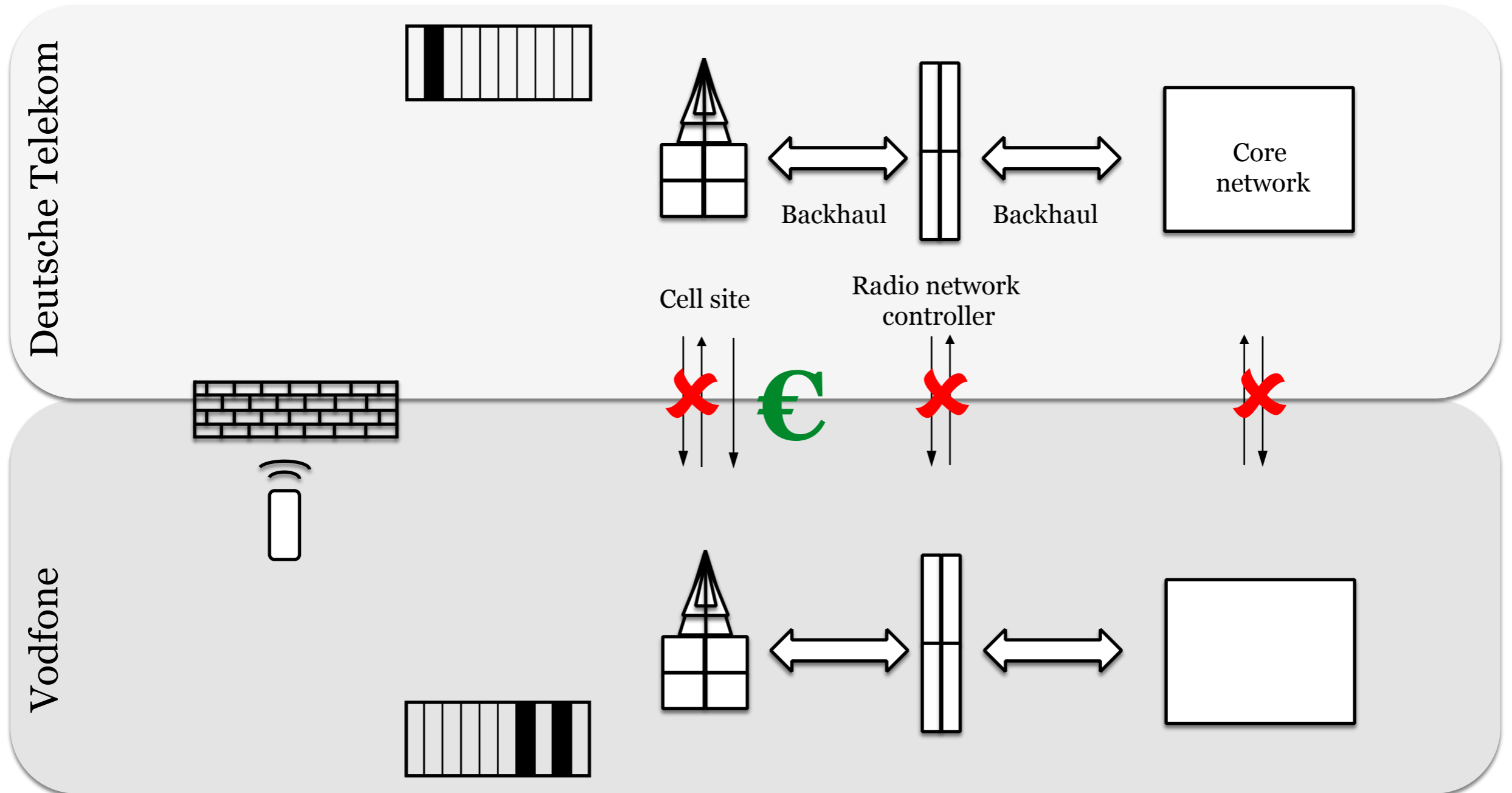
Service Trading



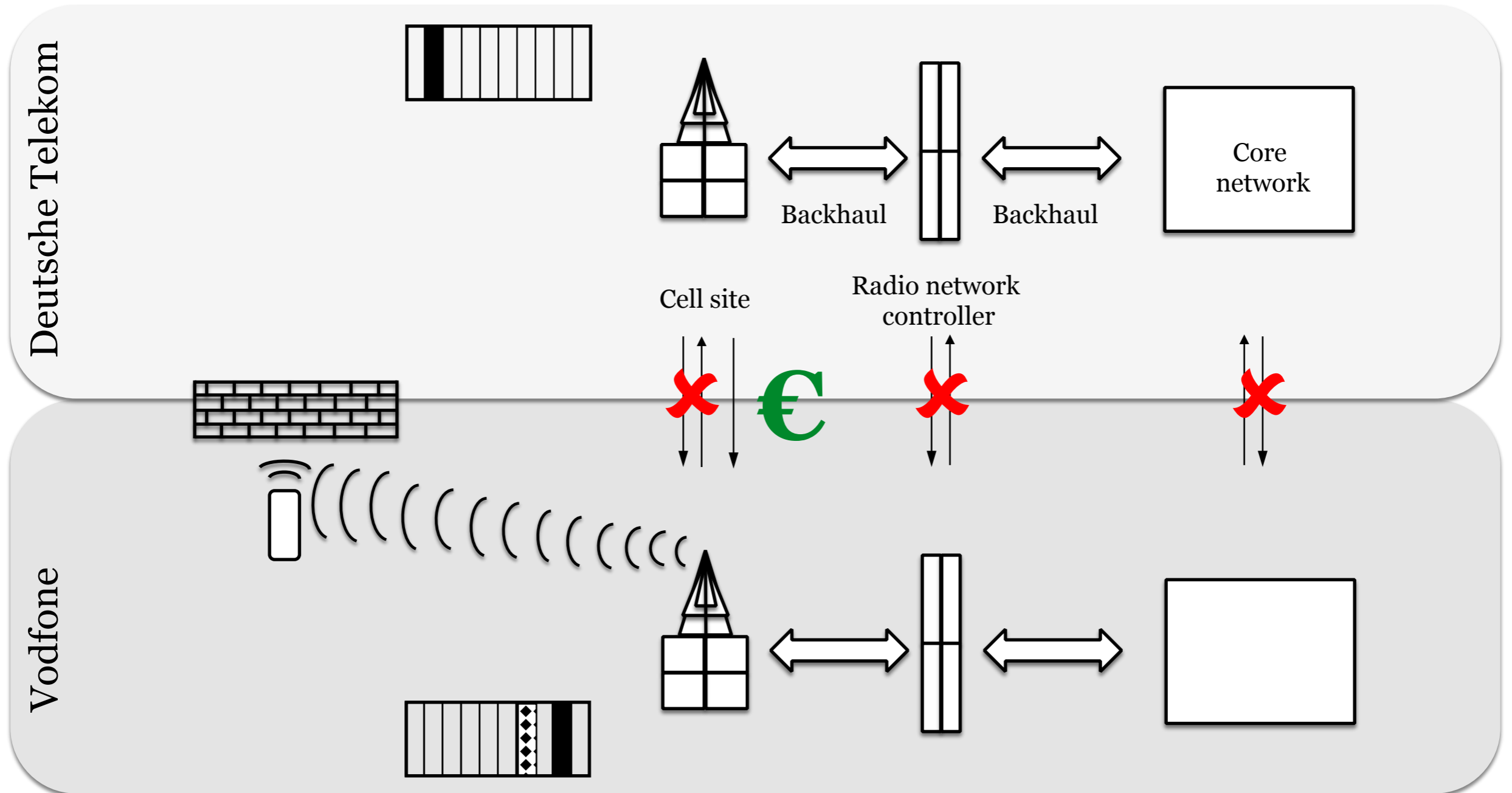
Service Trading



Service Trading



Service Trading



Overall Conclusions

- Resource allocation in **heterogeneous interference networks** for 5G and beyond includes
 - **Resource sharing** between different networks or operators
 - **Multi-objective programming** to trade off conflicting metrics, e.g., throughput, secrecy, and latency
- The **sharing gains** are realised on **network layer** while the **interference/leakage** is observed at **physical layer**

Ongoing and Future Work

- **Implementation** of service trading on the ns3 platform (algorithm design and analysis)
- Connect **energy efficiency** analysis and optimisation with **resource trading** algorithm
- Apply to **real measured** (big) **data** obtained from deployed cellular network and verify gains (throughput and latency)
- Include **physical layer security** in the resource trading algorithms
- Demonstrate physical layer security strategies on **demonstrators** and verify **feasibility**
- Embed the developed algorithm into **network slicing**