Energy-Neutral System-Level Analysis and Optimization of 5G Wireless Networks

(energy harvesting and wireless power transfer)

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H2020-MCSA

5Gwireless

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Energy Neutrality – Part II

Energy-neutral network: A self-sustained network, that is able to operate without requiring energy from the electrical supply.

Very ambitious goal, which requires two components:

- **Energy efficiency** to make an efficient use of the available energy.
- **Energy harvesting** to obtain new energy as the available reserves are being used.

The tutorial will focus on both aspects.

- The first half of the tutorial will discuss the techniques to maximize the network energy efficiency.
- The second half of the tutorial will discuss the approaches to harvest new energy to be used in the network.

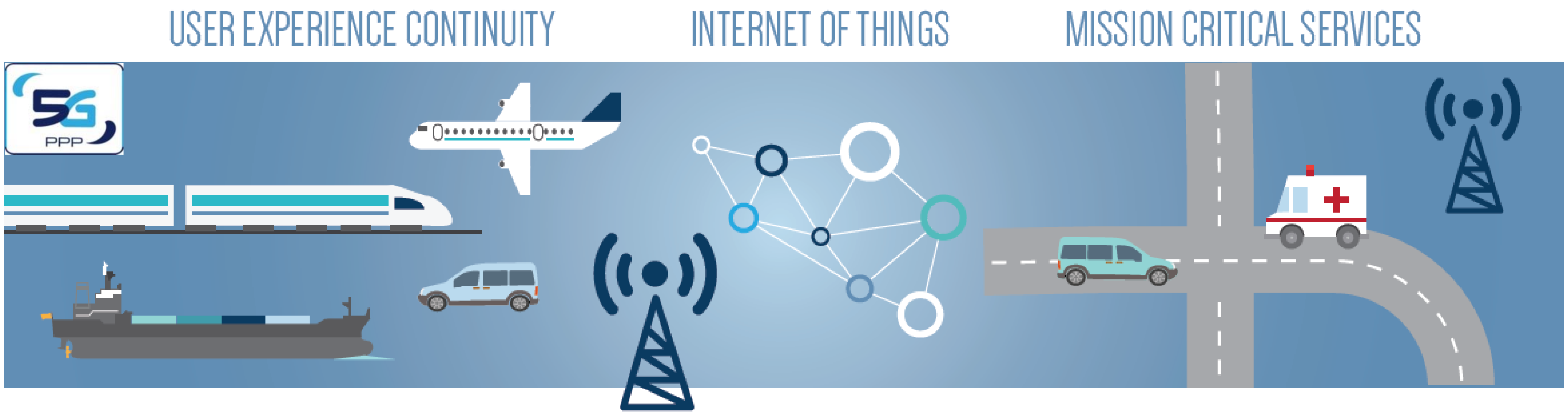
Both parts will focus on 5G applications and scenarios

5G-PPP – 5G Network Vision

More information at
www.5g-ppp.eu

5G-PPP 5G Vision Document, "The next-generation of communication networks and services", March 2015. Available: http://5g-ppp.eu/wp-content/uploads/2015/02/5G-Vision-Brochure-v1.pdf.

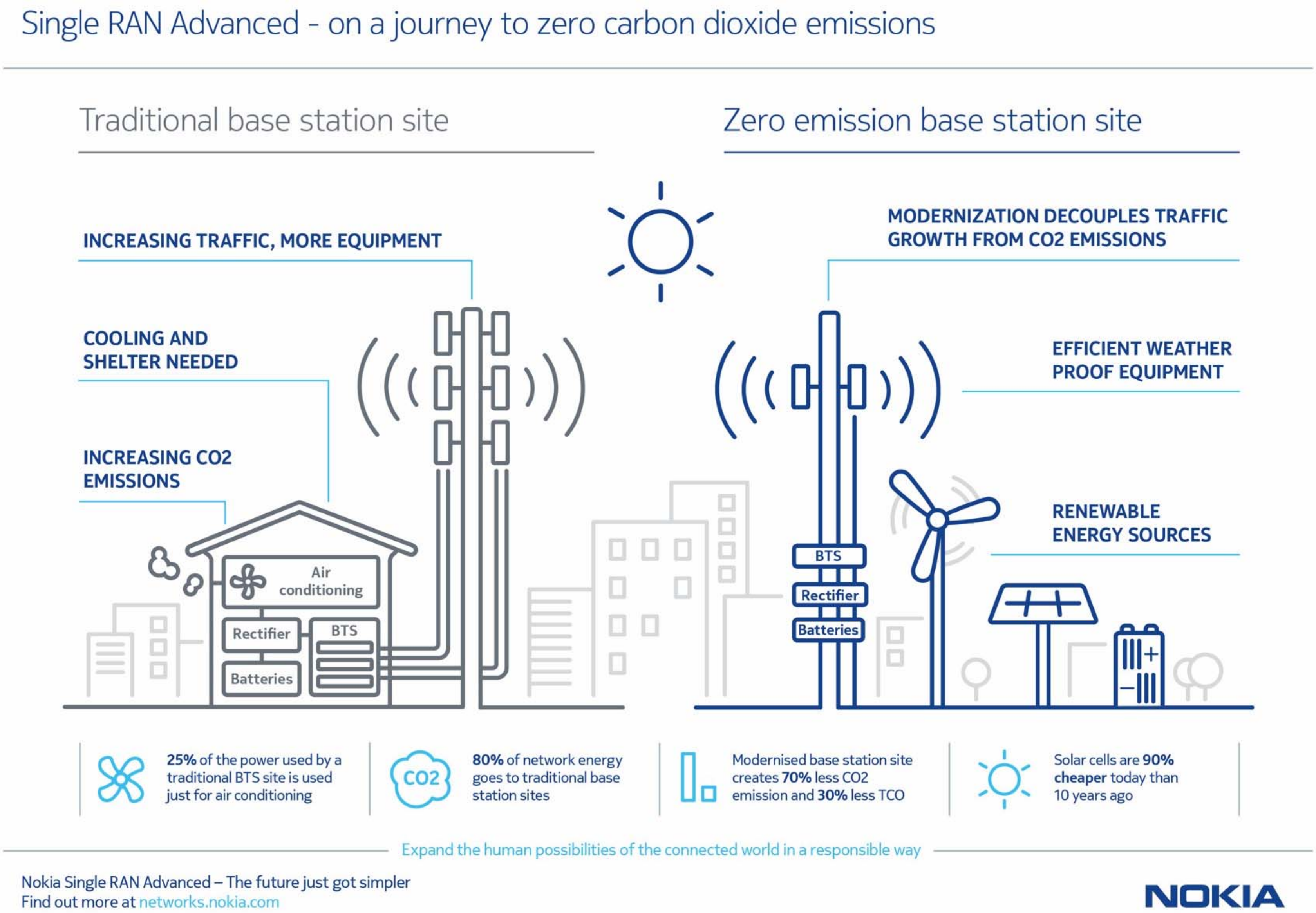
5G-PPP – 5G New Service Capabilities



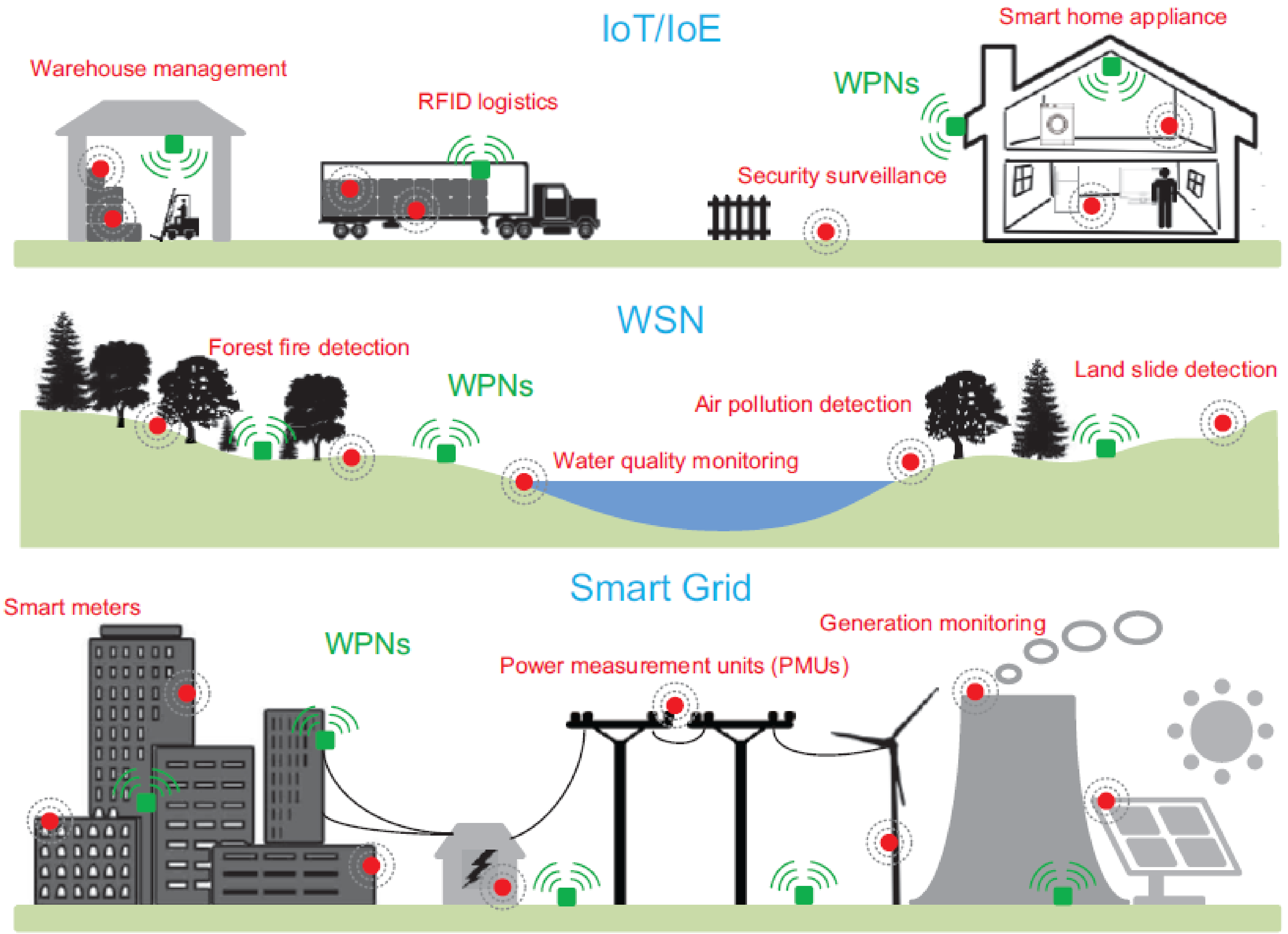
- **5G-PPP in a nuthsell:**
  - To conduct research and innovation work that will form the basis of the 5G infrastructure for the Future Internet for a wide range of applications
  - 5G is a key enabler for the IoT, providing a platform to connect a massive number of sensors, devices, actuators with stringent energy and transmission constraints
  - 5G will be designed to be a sustainable and scalable technology
  - 5G will bring drastic energy efficiency improvement and harvest energy from everywhere, solar, thermal, vibration and electromagnetic (RF) sources

5G-PPP 5G Vision Document, "The next-generation of communication networks and services", March 2015. Available: http://5g-ppp.eu/wp-content/uploads/2015/02/5G-Vision-Brochure-v1.pdf.

Energy-Neutral Cellular Base Stations …



… and Beyond Cellular …



S. Bi, C. K. Ho, and R. Zhang, "Wireless powered communication: Opportunities and challenges", IEEE Commun. Mag., vol. 53, no. 4. pp. 117–125, Apr. 2015.

The 5G (Cellular) Network of the Future

- **Buzzword 1: Densification**
  1. **Access Points (Network Topology, HetNets)**
  2. **Radiating Elements (Large-Scale/Massive MIMO)**

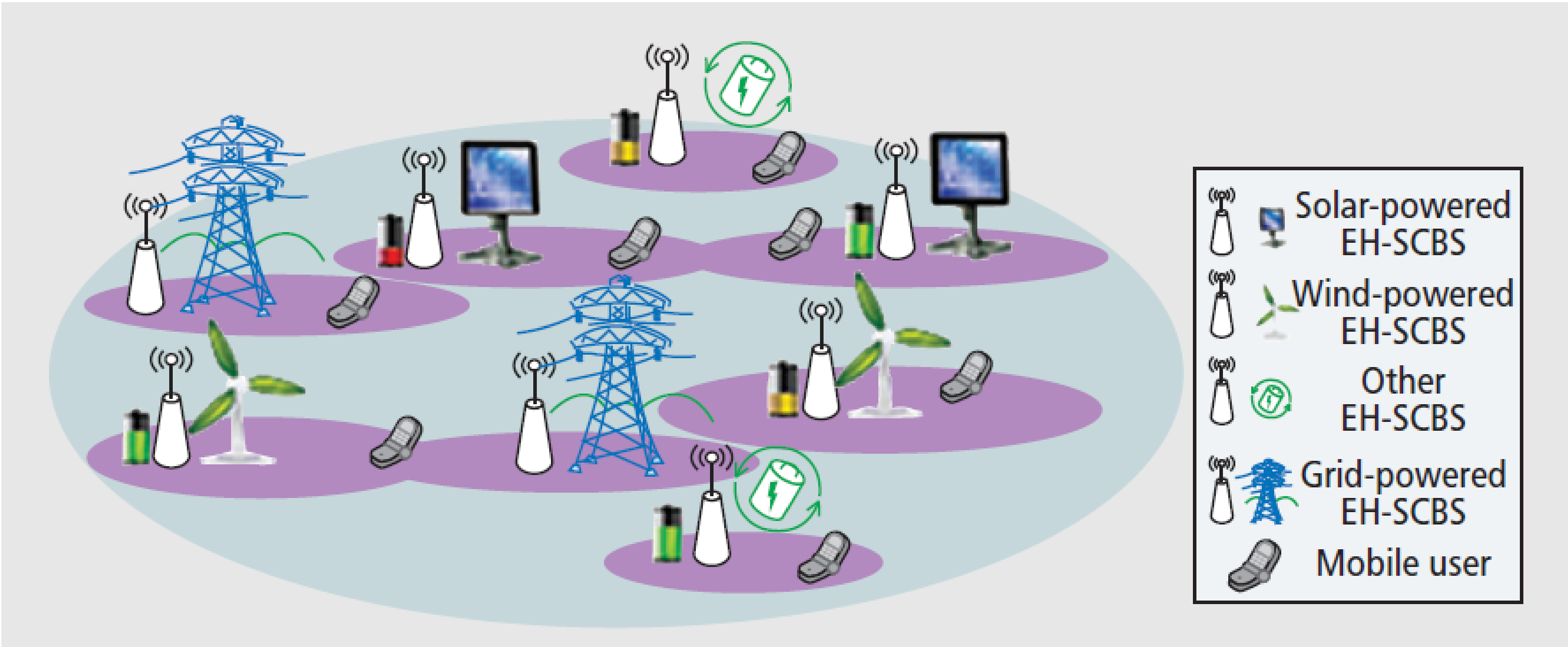
- **Buzzword 2: Spectral vs. Energy Efficiency Trade-Off**
  1. **Shorter Transmission Distance (Relaying, Femto, D2D)**
  2. **Total Power Dissipation (Single-RF MIMO, Antenna Muting)**
  3. ***RF Energy Harvesting*, *Wireless Power Transfer*, Full-Duplex**

- **Buzzword 3: Spectrum Scarcity**
  1. **Cognitive Radio and Opportunistic Communications**
  2. **mmWave Cellular Communications**

- **Buzzword 4: Software-Defined, Centrally-Controlled, Shared, Virtualized**
  1. **SDN, NFV, Network Resource Virtualization (NRV)**

Wireless Power Transfer & Energy Harvesting

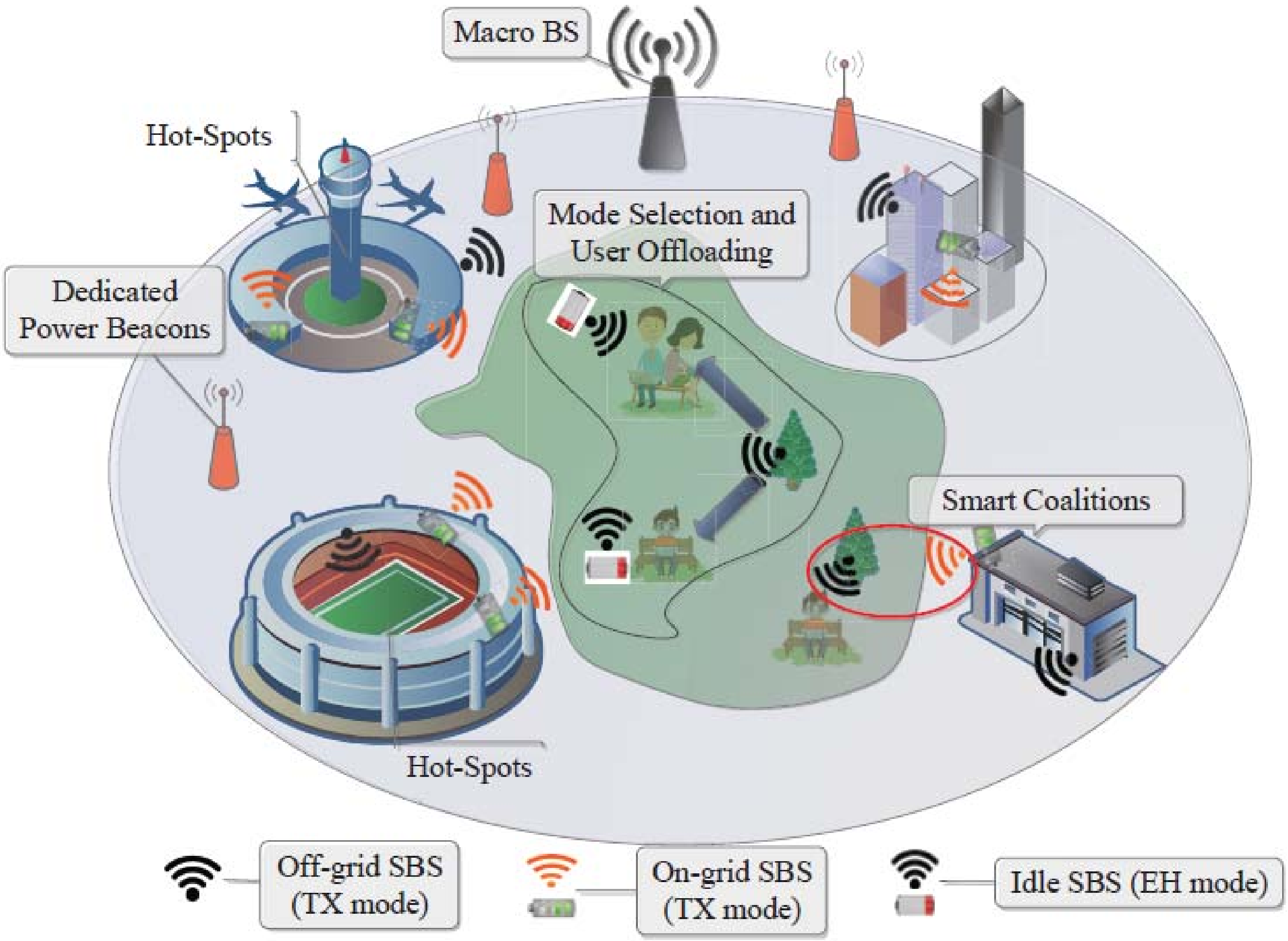
… Potential / Futuristic Scenarios based on Renewable Energy …



Y. Mao, Y. Luo, J. Zhang, and K. B. Letaief, "Energy Harvesting Small Cell Networks: Feasibility, Deployment, and Operation", IEEE Commun. Mag., June 2015.

Wireless Power Transfer & Energy Harvesting

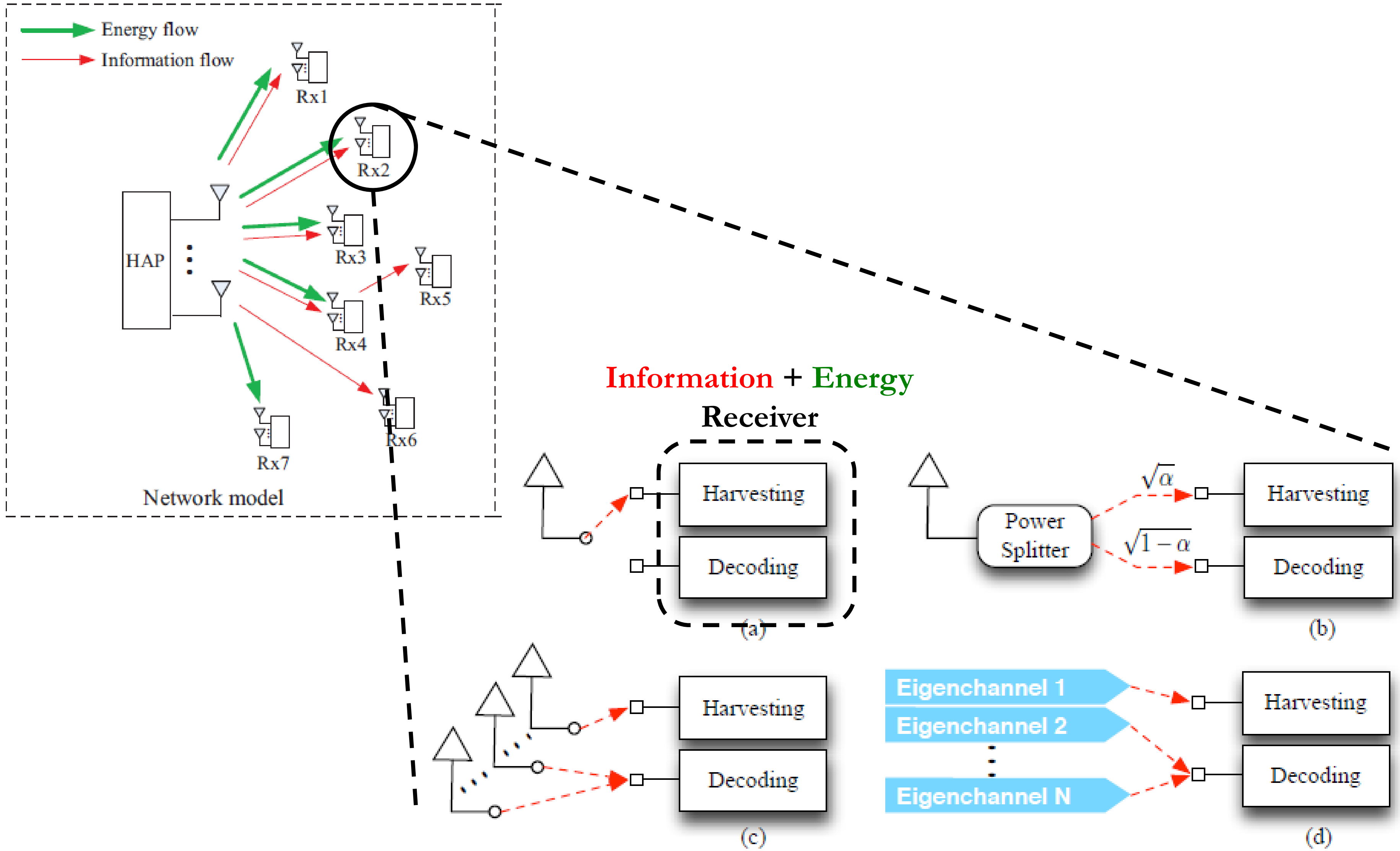
… Potential / Futuristic Scenarios based on RF Power Transfer …



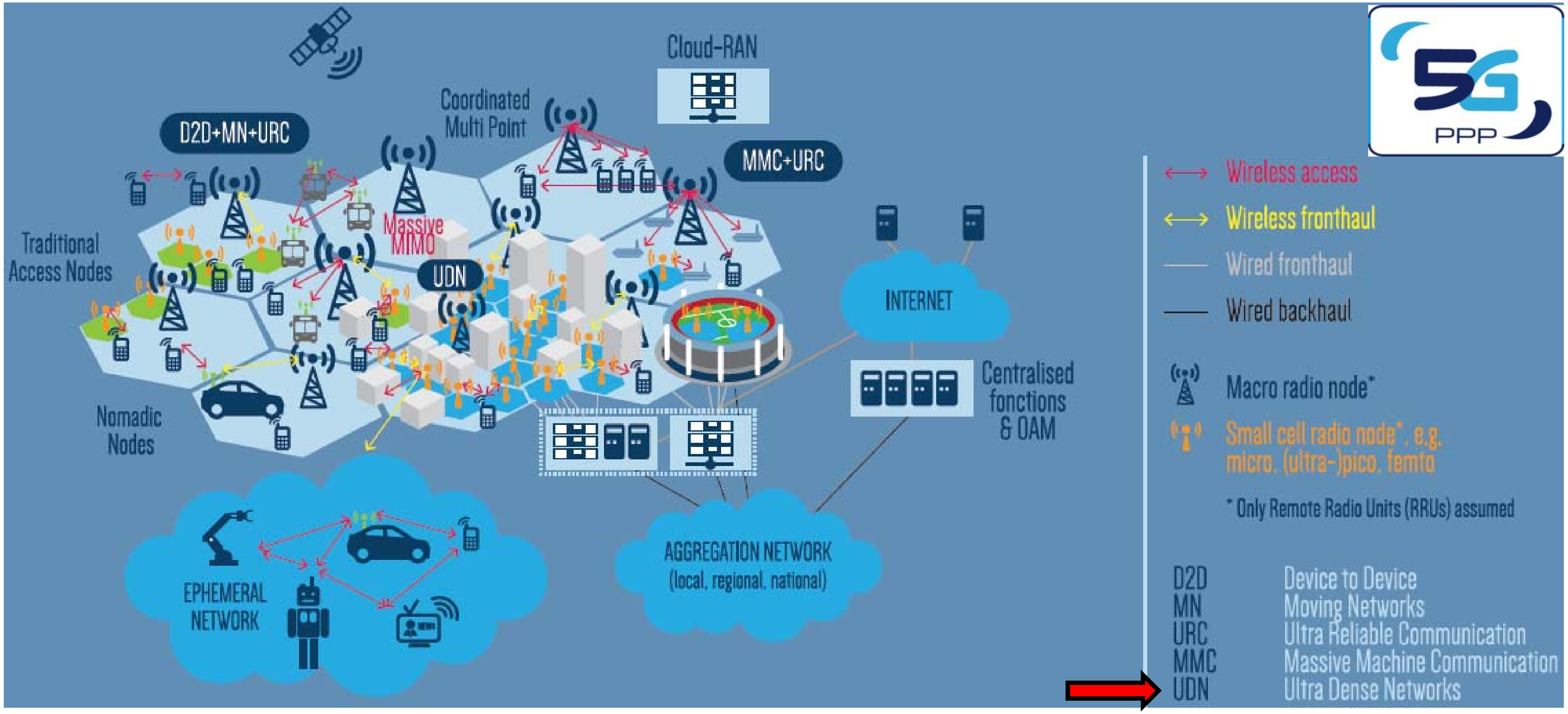
A. Ghazanfari, H. Tabassum, and E. Hossain, "Ambient RF Energy Harvesting in Ultra-Dense Small Cell Networks: Performance and Trade-offs", IEEE Wireless Commun. Mag., Apr. 2015.

Wireless Power Transfer – RF Energy Harvesting

SWIPT: Simultaneous Wireless Information and Power Transfer



Why Now? Is it Feasible?



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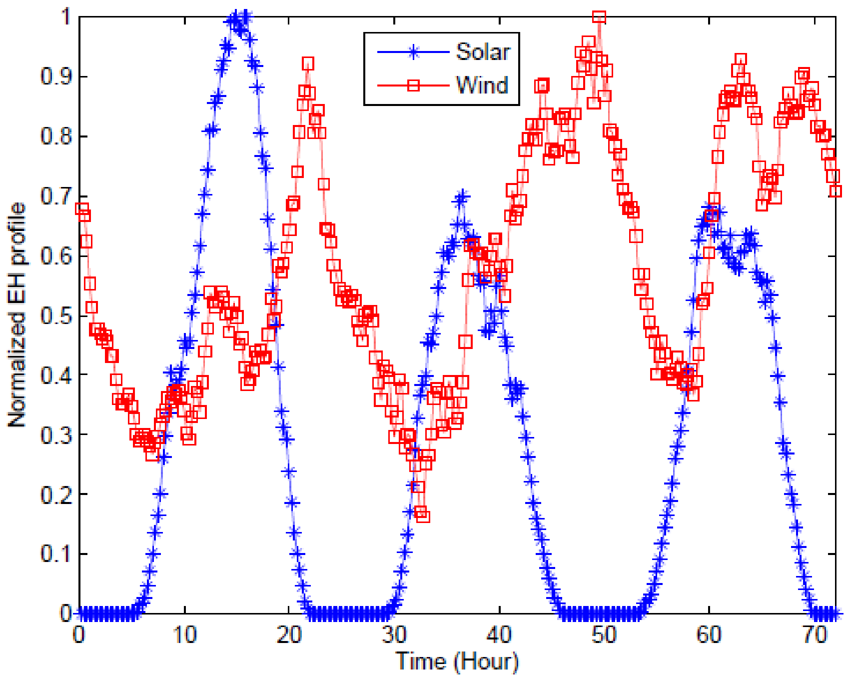
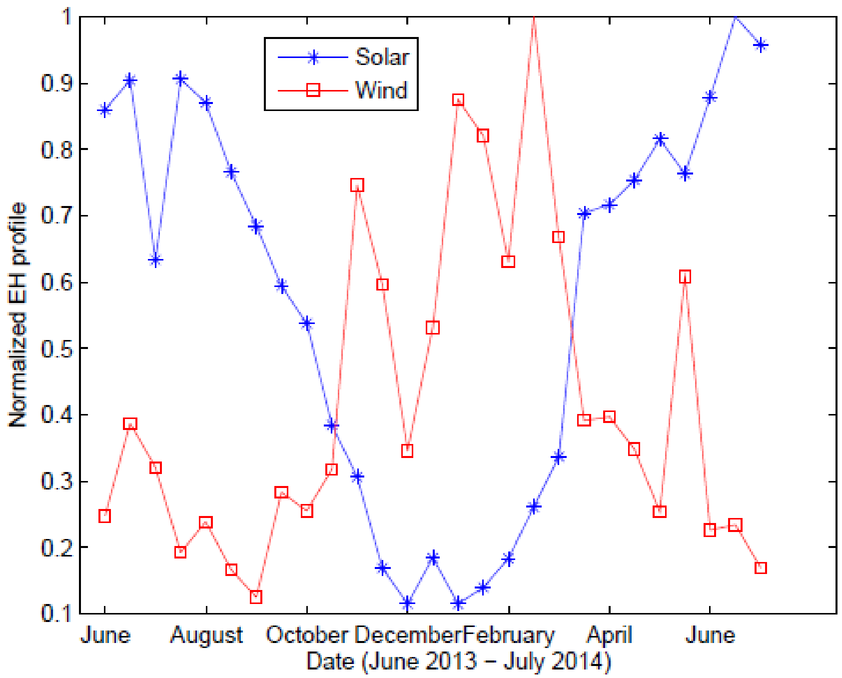


(a) Short time horizon.



(b) Long time horizon.

- **SOLAR and WIND can provide the necessary electric power to Small Cells**
  - **100 W electric power can be generated by a 121 cm x 53.6 cm solar panel under sunlight radiation or by a rotor with a 1 m diameter under an 8 m/s wind speed**
  - **They nicely complement each other over a short and a long term horizons**

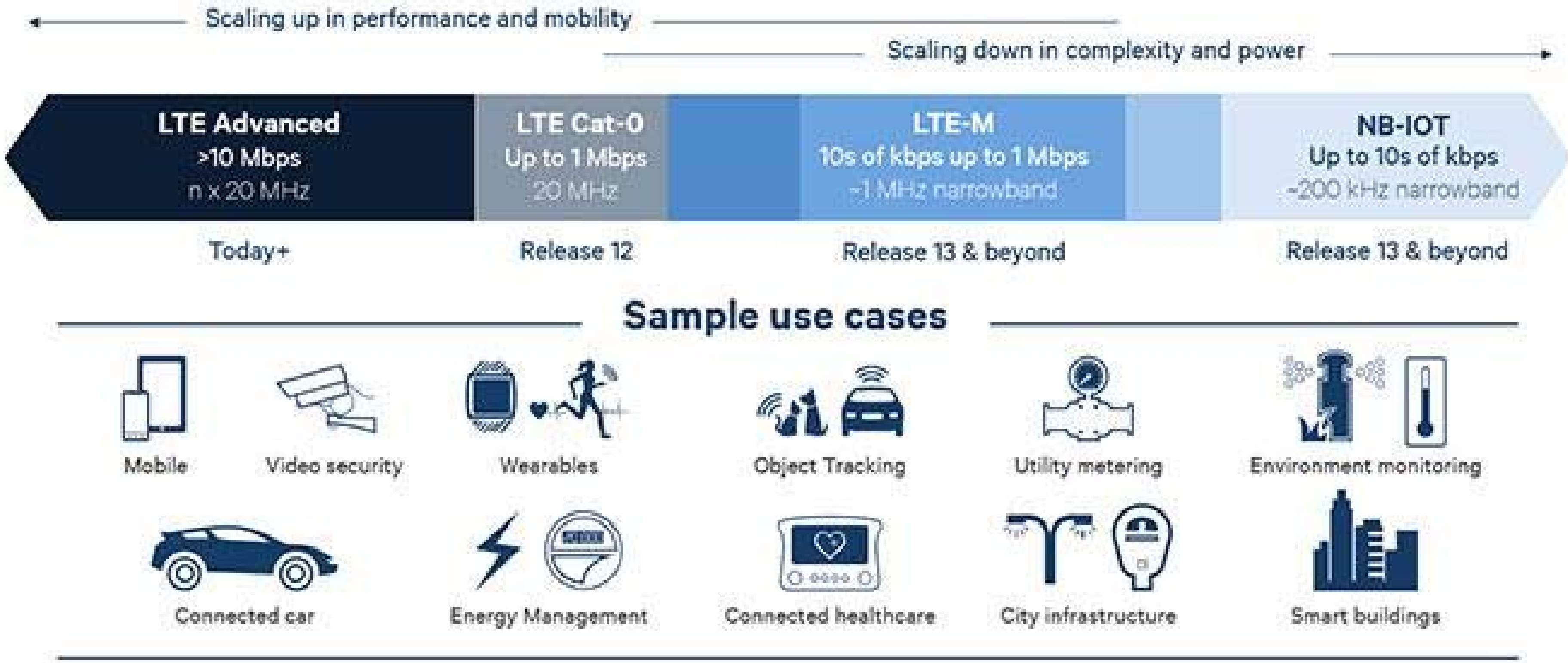
Elia, Power generation, available online at http://www.elia.be/en/grid-data/power-generation.

Solar Powered BSs Exist…

Figure 1. Worldwide deployment status of solar powered base stations at the end of 2014 [4]. The number in the circles indicate the number of solar powered BSs in a particular country.

V. Chamola and B. Sikdar, "Solar Powered Cellular Base Stations: Current Scenario, Issues and Proposed Solutions", IEEE Commun. Mag., May 2016.

Very Recent Developments: NB-LTE for IoT



Very Recent Developments: NB-LTE for IoT

WHAT'S THAT?

- NB-LTE is one of the proposed "clean slate" options for adapting LTE technology to make it suitable for low cost, low power, wide area networks for IoT applications

- NB-LTE is one of the 4G LTE variants being looked at for IoT. Standards body 3GPP is studying no less than four possible ways to adapt 4G LTE to make it suitable for low power wide area IoT networks

WHY THAT?

- NB-LTE is well-suited for the IoT market segment "because of its low implementation cost, ease of use and power efficiency"

- Cellular networks already cover 90 percent of the world's population so it makes sense to leverage this global footprint to support and drive IoT adoption through the standardization of NB-LTE

Very Recent Developments: Freevolt Technology

WHAT'S THAT?

- A patented technology developed by an international team from Drayson Technologies and Imperial College London
- Drayson Technologies claims to be the first to market this technology, which was recently commercially licensed (PA Consulting Group was granted it)

HOW IT WORKS?

- Freevolt harvests indoor & outdoor ambient RF waves across multiple bands and uses the energy to power low energy electronic devices
- Freevolt is able to pick up unused electro-magnetic energy from sources such as mobile cellular networks and Wi-Fi without the need for charging by cable or a dedicated transmitter
- Freevolt can harvest this energy without interrupting the data signal. The type of devices it is able to power will depend the device's energy budget, form factor and the amount of available ambient radio energy
- The range of possible applications is endless, but IoT sensors, beacons and wearables, such as fitness bands, clothing and medical garments, are obvious markets. The company has developed a commercially available personal air pollution sensor called CleanSpace Tag

Very Recent Developments: Freevolt Technology

CleanSpace™ Tag

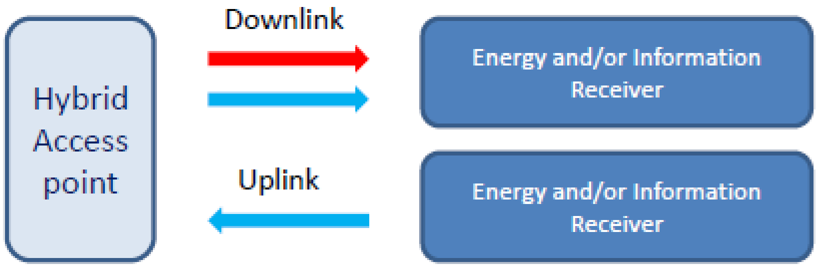
The first commercial application of our revolutionary new Freevolt technology is the CleanSpace™ Tag, a personal air quality pollution sensor. It uses energy from wireless signals, such as WiFi and Mobile Phone Networks, to charge the Tag. It will never have to be plugged in to charge or change its batteries for its lifetime - a world first from Drayson Technologies.

Tag

The CleanSpace™ Tag gives members of the CleanSpace™ Movement actionable, personal, air quality data (specifically carbon monoxide) and by crowd sourcing that data, provides a highly effective air quality network.

Air pollution is a growing concern, especially in our major cities and its impact on an individual's health is a well-documented issue.

SWIPT – System-Level Modeling and Optimization



Major Difference:

Information (rate) and harvesting (energy) requirements need to be jointly satisfied

Setup: LOS/NLOS, beamforming, etc.

Harvesting: Interference is GOOD

$$\mathcal{Q} = \eta\zeta\left(\mathrm{U}^{(0)} + \mathrm{I}_{\mathrm{agg}}\right)$$

Information: Interference is BAD

$$\mathcal{R} = \mu \mathrm{B}_{\mathrm{W}} \log_2\left(1 + \frac{\mathrm{U}^{(0)}}{\sigma_{\mathrm{N}}^2 + \sigma_{\mathrm{C}}^2 + \mathrm{I}_{\mathrm{agg}}}\right)$$

Joint Statistical Characterization of Harvested Energy and Achievable Rate in the Presence of Other-Cell Interference

$$\mathcal{F}_{\mathrm{c}}\left(\mathcal{Q}_0, \mathcal{R}_0\right) = \Pr\left\{\mathcal{Q} \ge \mathcal{Q}_0, \mathcal{R} \ge \mathcal{R}_0\right\}$$

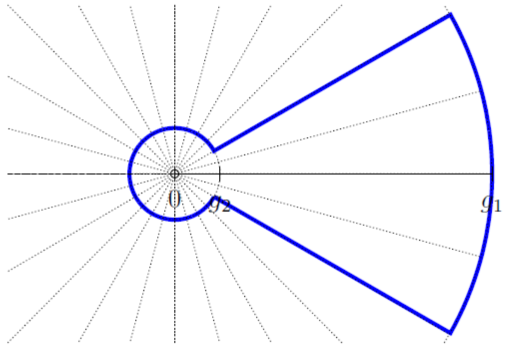
$$\mathcal{F}_{\mathrm{c}}\left(\mathcal{Q}_0, \mathcal{R}_0\right) \approx \int_0^{\mathcal{M}} \left[\int_0^{+\infty} (\pi\omega)^{-1} \operatorname{Im}\left\{\mathcal{Y}(\omega, x)\, \Phi_{\mathrm{I}_{\mathrm{agg}}}^{(\mathrm{RP})}(\omega | x)\right\} f_{P^{(0)}}(x)\, d\omega\right] dx$$

M. Di Renzo and W. Lu, "System-Level Analysis of Cellular Networks with Simultaneous Wireless Information and Power Transfer: Stochastic Geometry Modeling", IEEE Trans. Vehicular Technol., IEEE Early Access.

SWIPT – System-Level Modeling

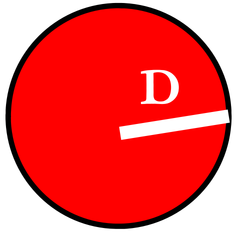
- **Directional beamforming**

$$g_{\mathrm{BS}}(\theta) = \begin{cases} G_{\mathrm{BS}}^{(\max)} & \text{if} \quad |\theta| \le \omega_{\mathrm{BS}}/2 \\ G_{\mathrm{BS}}^{(\min)} & \text{if} \quad |\theta| > \omega_{\mathrm{BS}}/2 \end{cases}$$



- **Accurate channel modeling: LOS/NLOS links**

$$p_s(r) = \begin{cases} q_s^{[0,D]} & \text{if} \quad r \in [0, D) \\ q_s^{[D,\infty]} & \text{if} \quad r \in [D, +\infty) \end{cases}$$



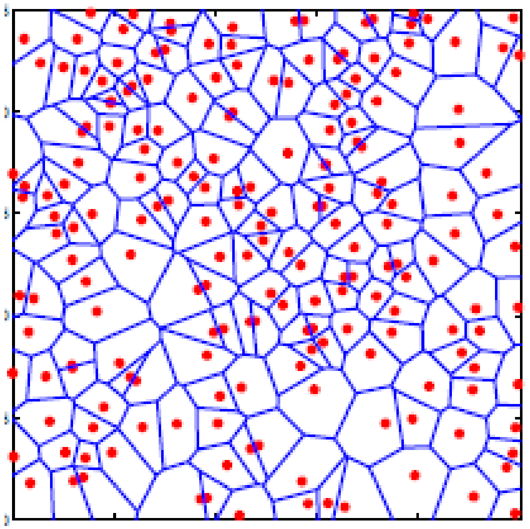
- **Cell association criterion: smallest path-loss**

$$L_s^{(0)} = \min_{n \in \Psi_s} \left\{ l_s\left(r^{(n)}\right) \right\} \qquad L^{(0)} = \min\left\{ L_{\mathrm{LOS}}^{(0)}, L_{\mathrm{NLOS}}^{(0)} \right\}$$

SWIPT – System-Level Modeling

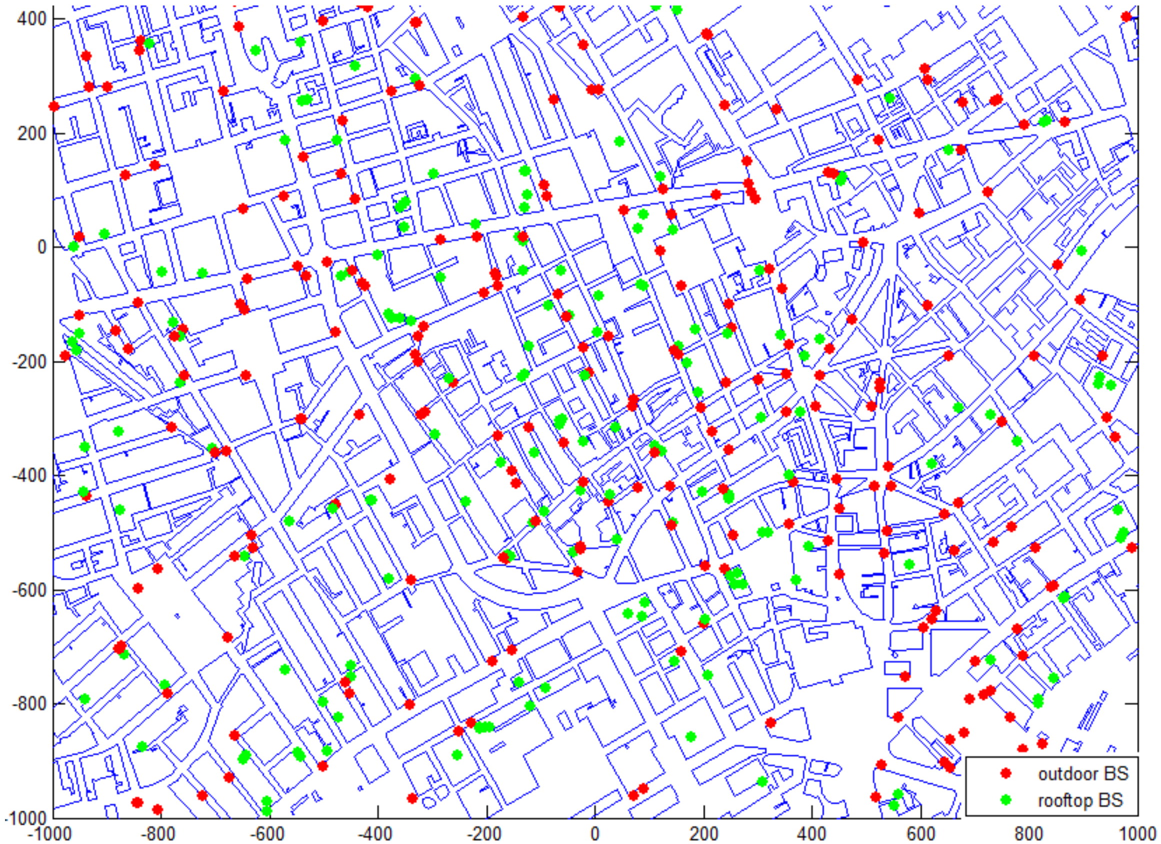
- Stochastic geometry is used for system-level analysis
- Experimental validation with actual BSs and building deployments

Modeling (PPP)



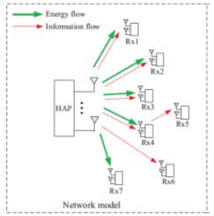
Completely random BSs

Validation (OFCOM + OS in London, UK)

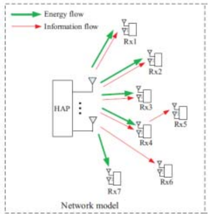


SWIPT – PPP + LOS/NLOS, etc…

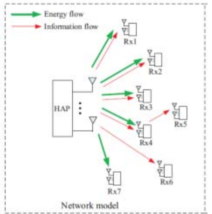
… not an easy mathematical problem …



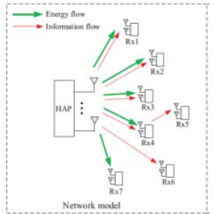
Network model



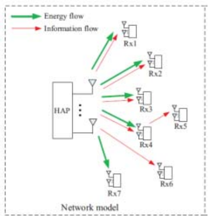
Network model



Network model



Network model



Network model

SWIPT – PPP + LOS/NLOS, etc…

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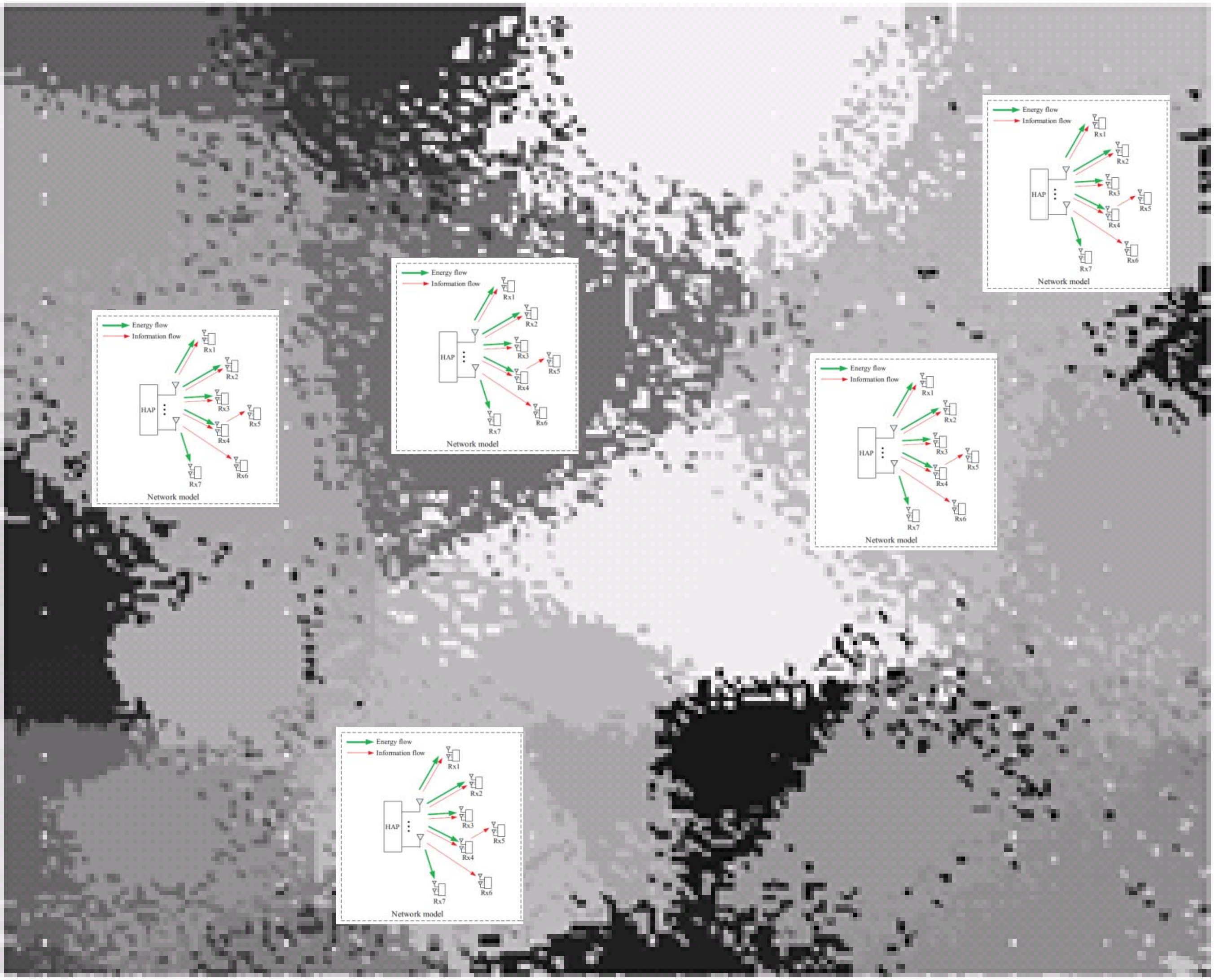
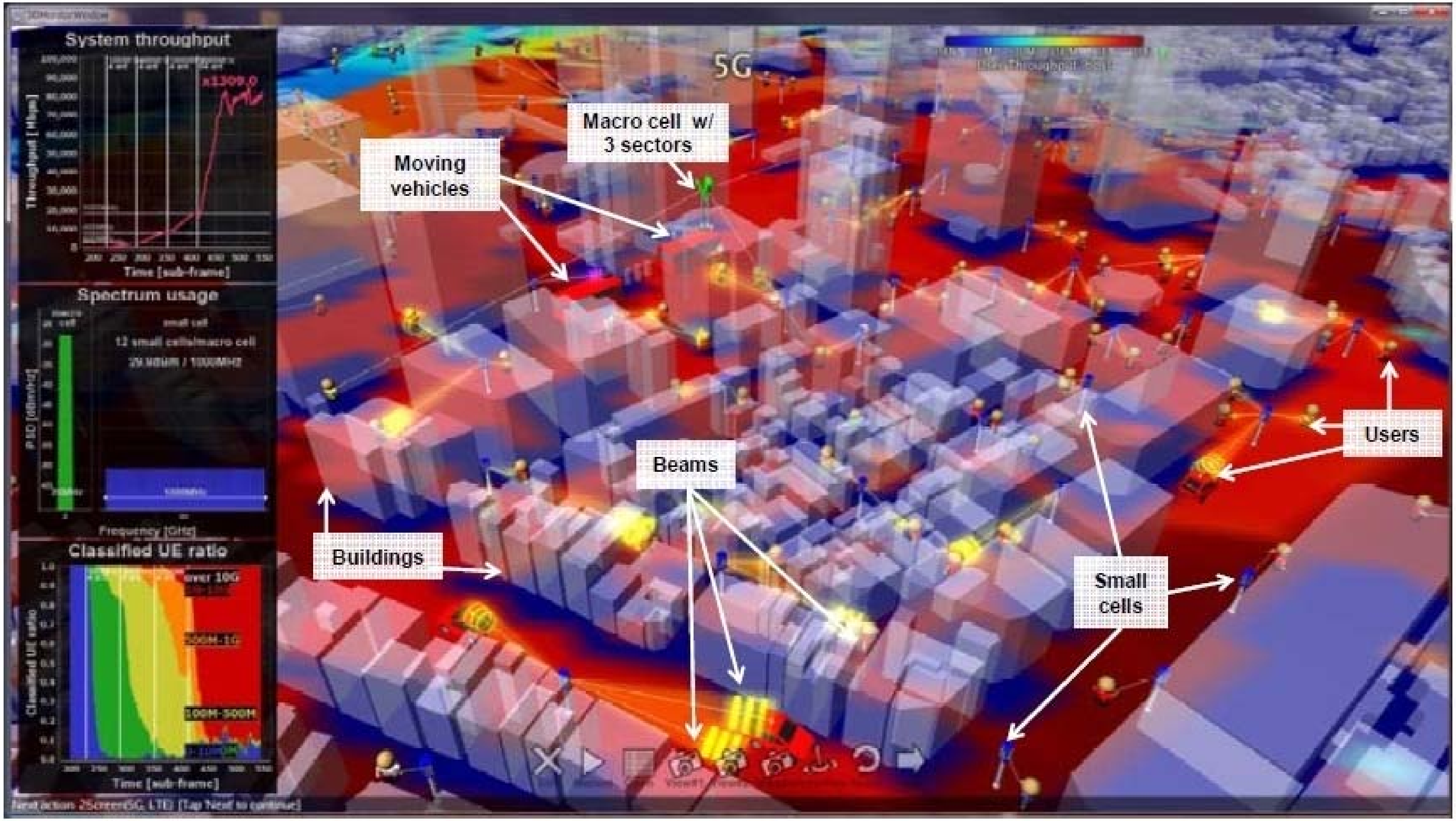


System-Level Modeling of Cellular Networks – Industry

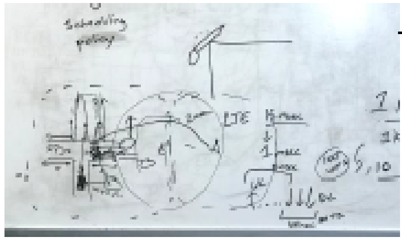
The NTT DOCOMO 5G Real-Time Simulator



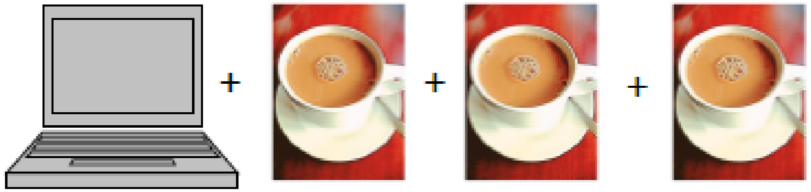
DOCOMO 5G White Paper, "5G Radio Access: Requirements, Concept and Technologies", July 2014.

Life of a 3GPP Simulation Expert (according to Samsung)

Inspiration strikes!



Weeks writing/debugging code:



There's a reason the server is called "grumpy":

```
[t.novlan@grumpy ~]$ bhosts
HOST_NAME          STATUS       JL/U    MAX  NJOBS
grumpy             unavail        -       1      0
mpisrv01dal        ok             -      24      5
mpisrv02dal        unavail        -       1      0
mpisrv03dal        ok             -      20     14
mpisrv04dal        ok             -      24     18
mpisrv05dal        ok             -      20      0
```

Come back after waiting this long:

```
runTime =

   1.4498e+05
```

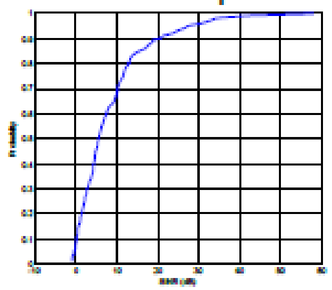
seconds!

Hope you don't find this:

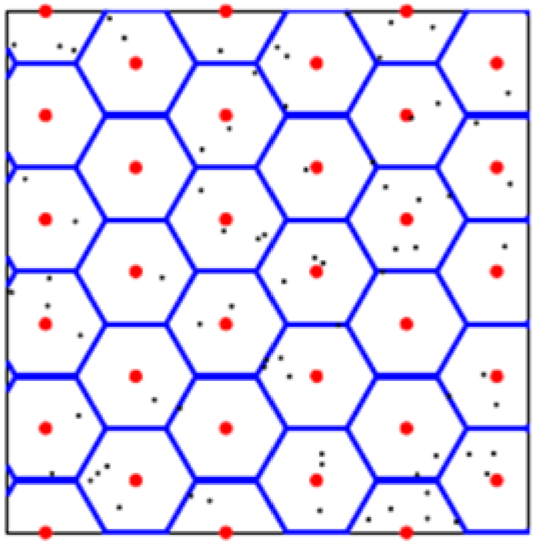
```
Segmentation violation detected-----
R8 = 000000002c81d6f5    R9 = 00002ac
_interpreter.so+02245206[   7] 0x0000
xa64/libmwm_interpreter.so+01923475[
13a/bin/glnxa64/libmwm_dispatcher.so-
[ 36] 0x00002ac2133eeb88 /opt/HW/app:
```

All for a few numbers and a MATLAB plot:

```
Buffer Occupancy
    Operator 1 (laa): 0.560
    Operator 2 (wifi): 0.607
UE Throughput (Mbps)
    Operator 1 (laa): 10.804
    Operator 2 (wifi): 8.708
Packet Latency (s)
    Operator 1 (laa): 0.606
    Operator 2 (wifi): 0.702
```



Modeling Cellular Networks – In Academia

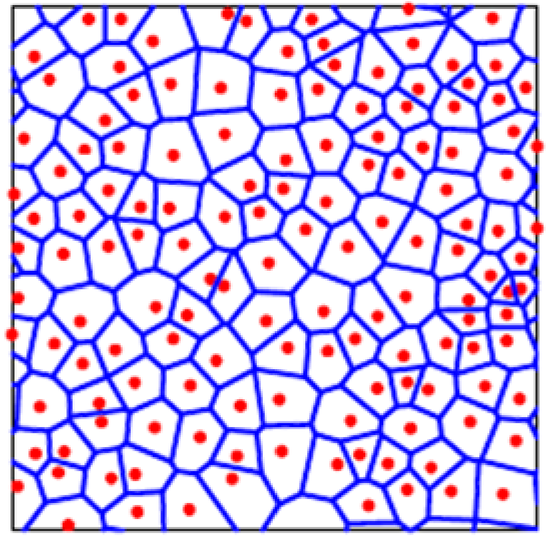


Traditional grid model

- Conventional approaches to the analysis and design of cellular networks (abstraction models) are:
  - The Wyner model
  - The single-cell interfering model or dominant interferers model
  - ***The regular hexagonal or square grid model***

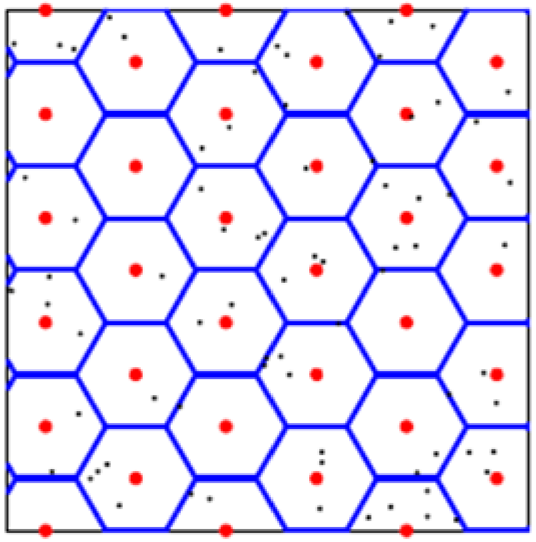
    D. H. Ring and W. R. Young, "The hexagonal cells concept", Bell Labs Technical Journal, Dec. 1947. http://www.privateline.com/archive/Ringcellreport1947.pdf.

Modeling Cellular Networks – In Academia



Actual 4G network today

Reality
vs.
Abstraction
Modeling



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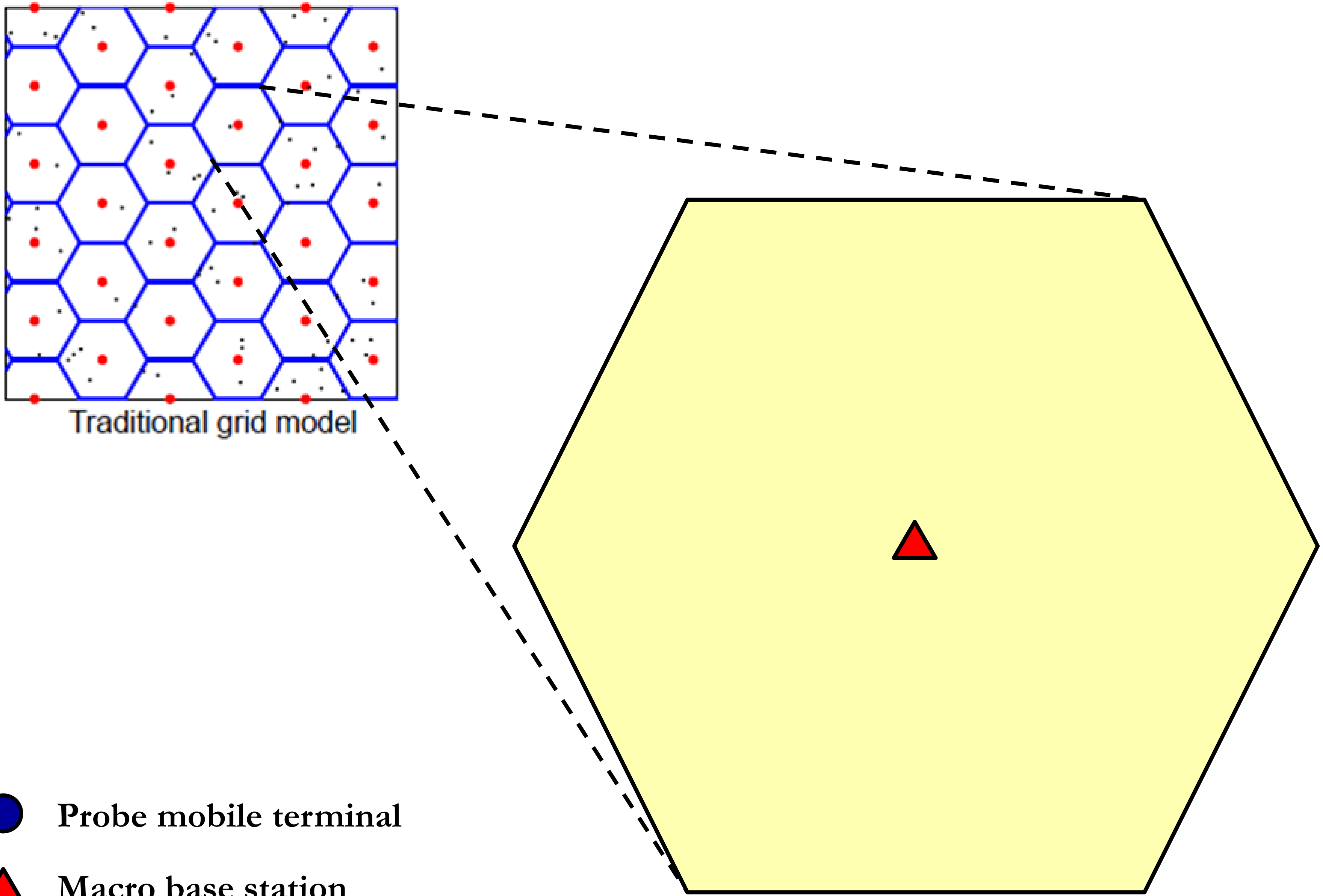
  D. H. Ring and W. R. Young, "The hexagonal cells concept", Bell Labs Technical Journal, Dec. 1947. http://www.privateline.com/archive/Ringcellreport1947.pdf.

The Conventional Grid-Based Approach

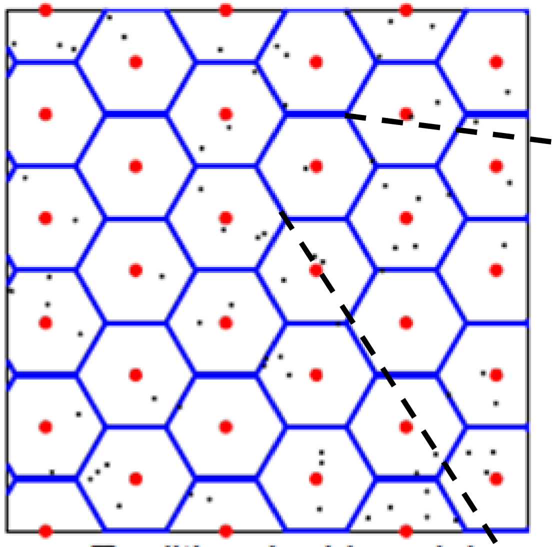


Traditional grid model

Probe mobile terminal

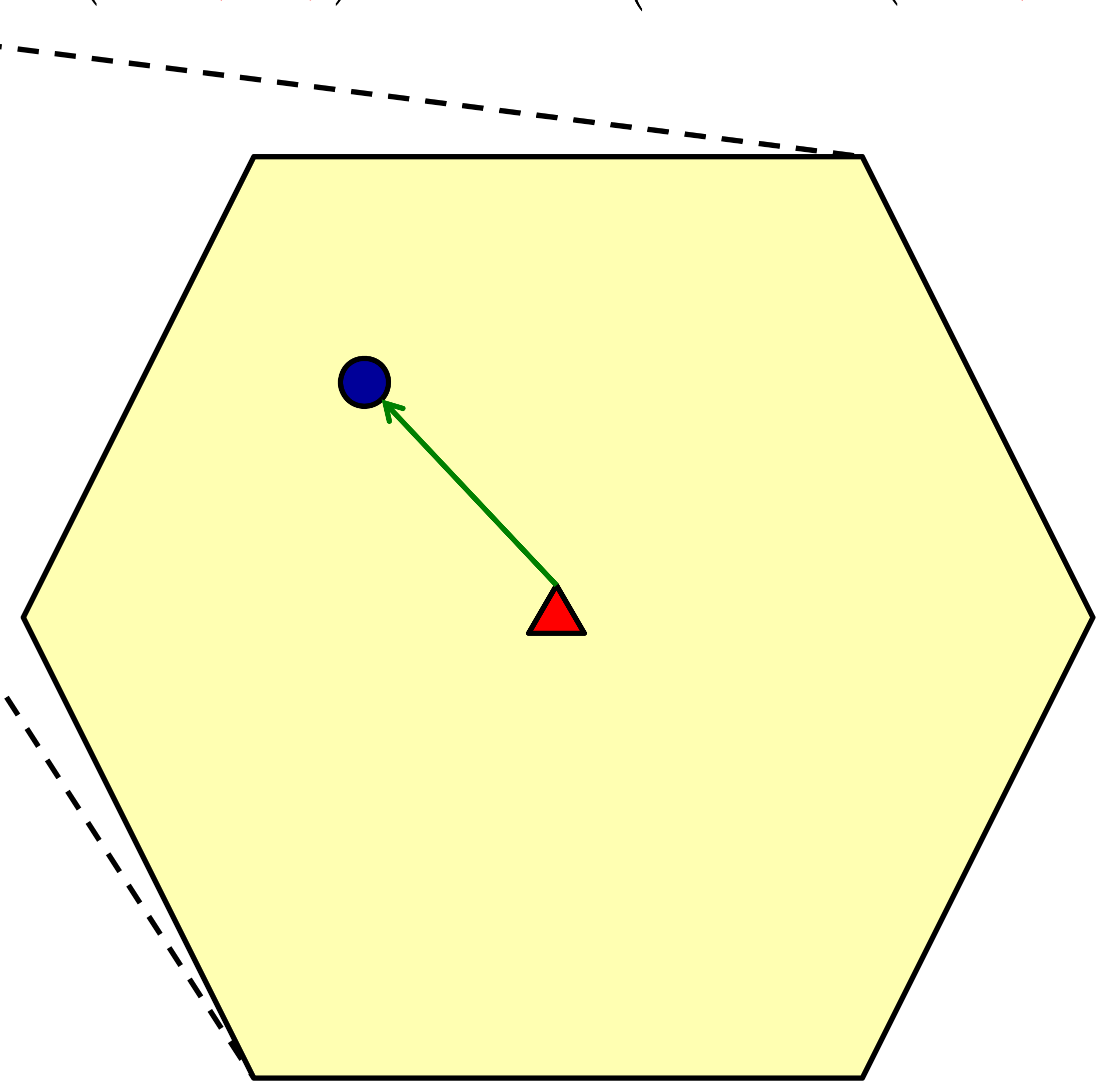
Macro base station

The Conventional Grid-Based Approach



Traditional grid model

$$C\left(r_0^{(1)},\left\{r_i^{(1)}\right\}\right)=\mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(1)},\left\{r_i^{(1)}\right\}\right)\right)$$

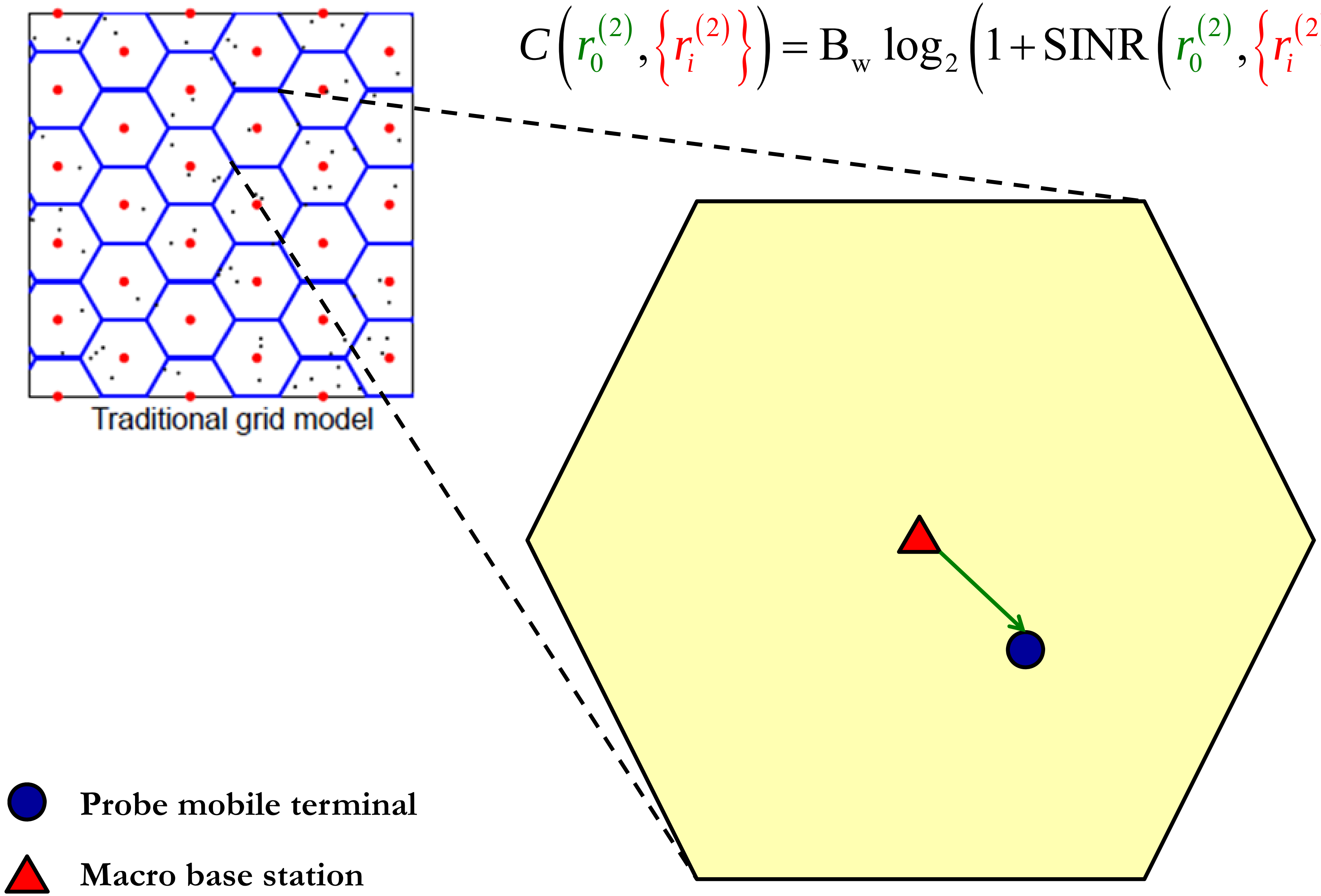


Probe mobile terminal

Macro base station

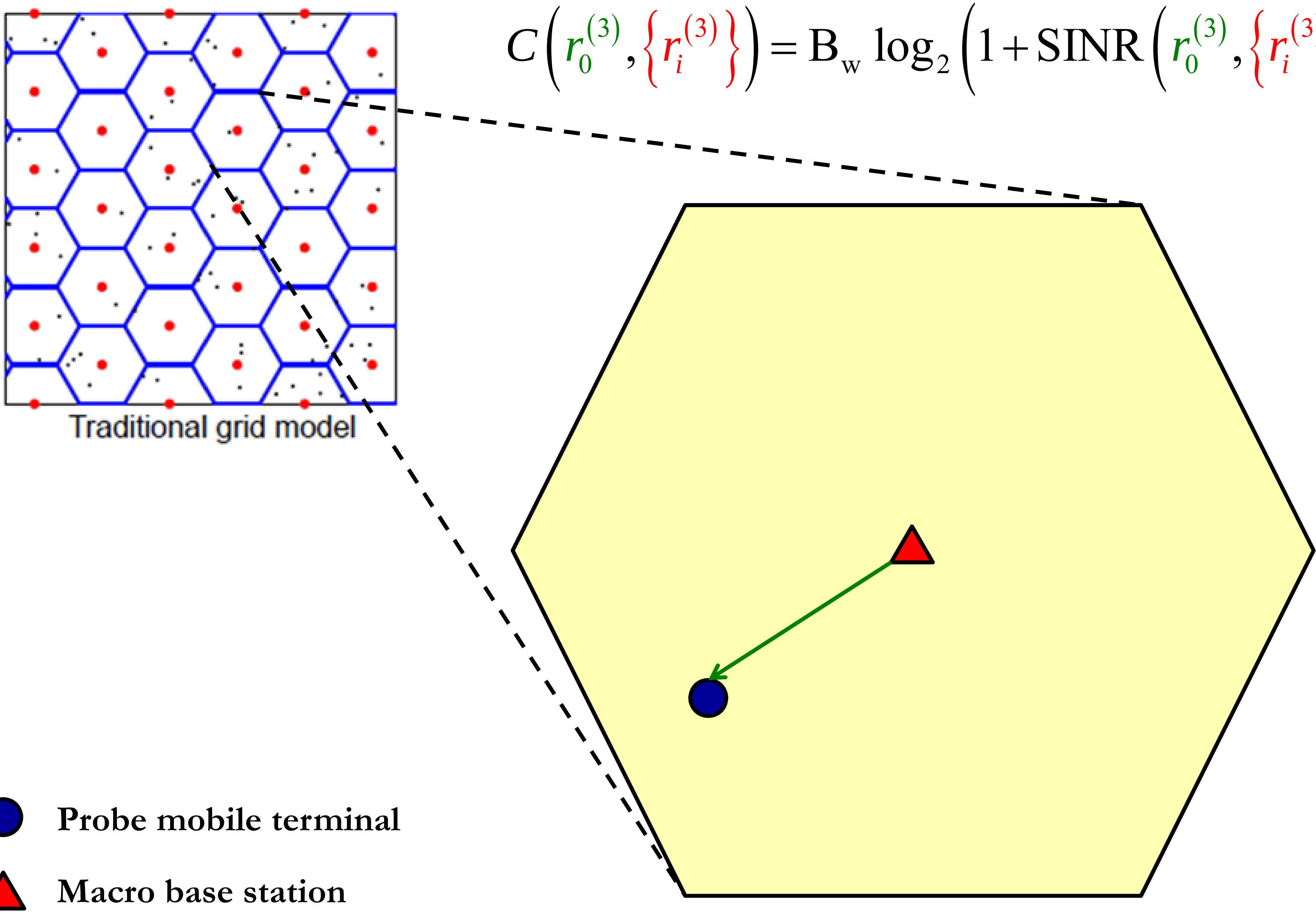
The Conventional Grid-Based Approach

$$C\left(r_0^{(2)},\left\{r_i^{(2)}\right\}\right)=\mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(2)},\left\{r_i^{(2)}\right\}\right)\right)$$



The Conventional Grid-Based Approach

$$C\left(r_0^{(3)},\left\{r_i^{(3)}\right\}\right)=\mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(3)},\left\{r_i^{(3)}\right\}\right)\right)$$



Traditional grid model

Probe mobile terminal

Macro base station

The Conventional Grid-Based Approach

$$\bar{C} = \mathrm{E}_{r_0,\{r_i\}}\left\{C\left(r_0,\left\{r_i\right\}\right)\right\} \approx \frac{1}{N}\sum_{n=1}^{N} C\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)$$

$$= \frac{1}{N}\sum_{n=1}^{N} \mathrm{B_w} \log_2\left(1+\mathrm{SINR}\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)\right)$$

The Conventional Grid-Based Approach

$$\bar{C} = \mathrm{E}_{r_0,\{r_i\}}\left\{C\left(r_0,\left\{r_i\right\}\right)\right\} \approx \frac{1}{N}\sum_{n=1}^{N} C\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)$$

$$= \frac{1}{N}\sum_{n=1}^{N} \mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)\right)$$

Simple enough… So, where is the issue?

The Conventional Grid-Based Approach

$$\bar{C} = \mathrm{E}_{r_0,\{r_i\}}\left\{C\left(r_0,\left\{r_i\right\}\right)\right\} \approx \frac{1}{N}\sum_{n=1}^{N} C\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)$$

$$= \frac{1}{N}\sum_{n=1}^{N} \mathrm{B_w} \log_2\left(1+\mathrm{SINR}\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)\right)$$

Simple enough… So, where is the issue?

The answer:

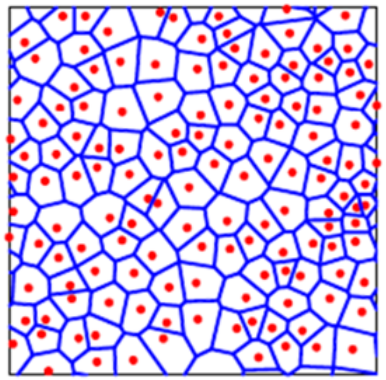
…this spatial expectation

cannot **be computed mathematically…**

The Conventional Grid-Based Approach: (Some) Issues

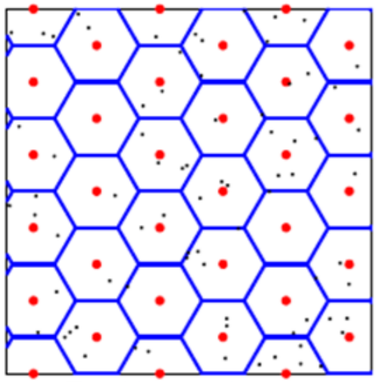
- **Advantages:**
  - Dozens of system parameters can be modeled and tuned in such simulations, and the results have been sufficiently accurate as to enable the evaluation of new proposed techniques and guide field deployments

- **Limitations:**
  - Actual coverage regions deviate from a regular grid
  - Mathematical modeling and optimization are not possible. Any elegant and insightful Shannon formulas for cellular networks?
  - The abstraction model is not scalable for application to ultra-dense HetNets (different densities, transmit powers, access technologies, etc…)

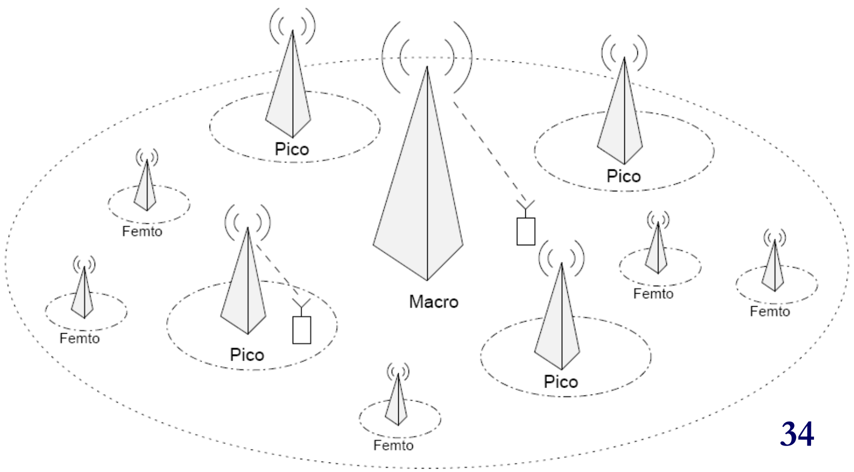


Actual 4G network today

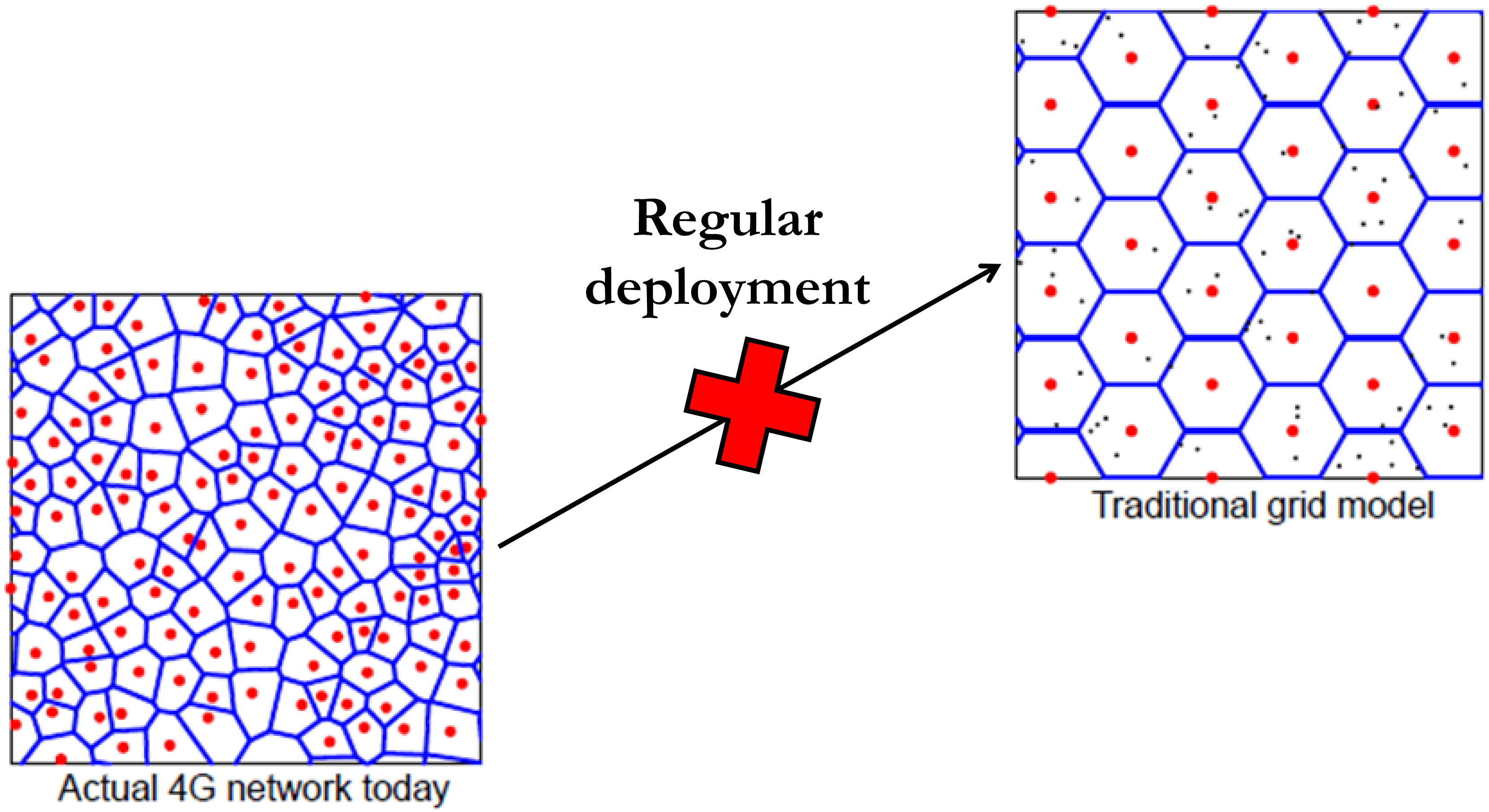
VS.



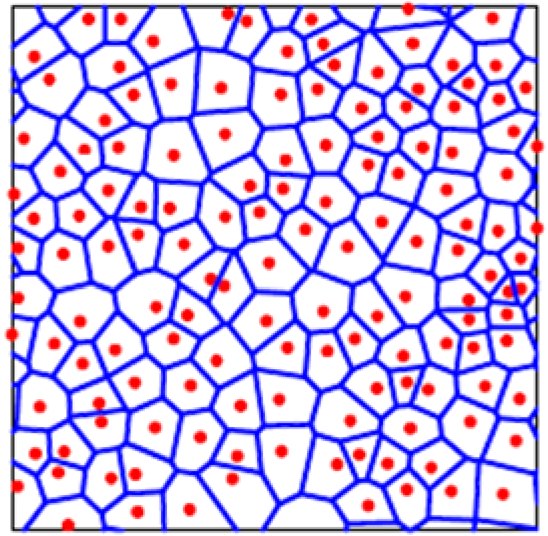
Traditional grid model



Let's Change the Abstraction Model, Then…

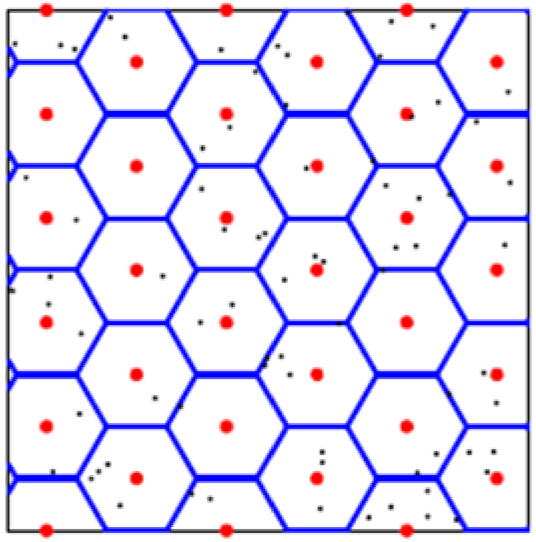


Let’s Change the Abstraction Model, Then…



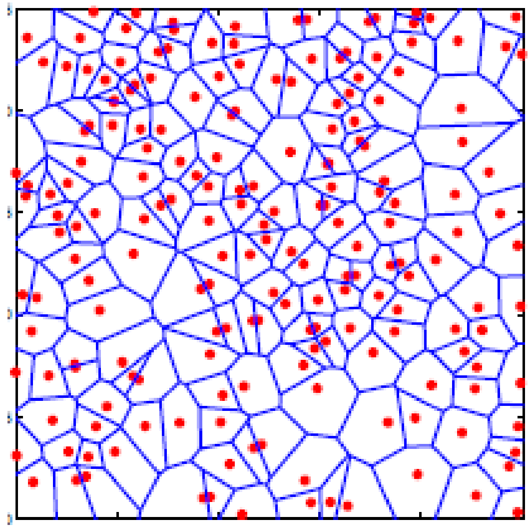
Actual 4G network today

Regular deployment ✗



Traditional grid model

Random deployment (PPP)



Completely random BSs

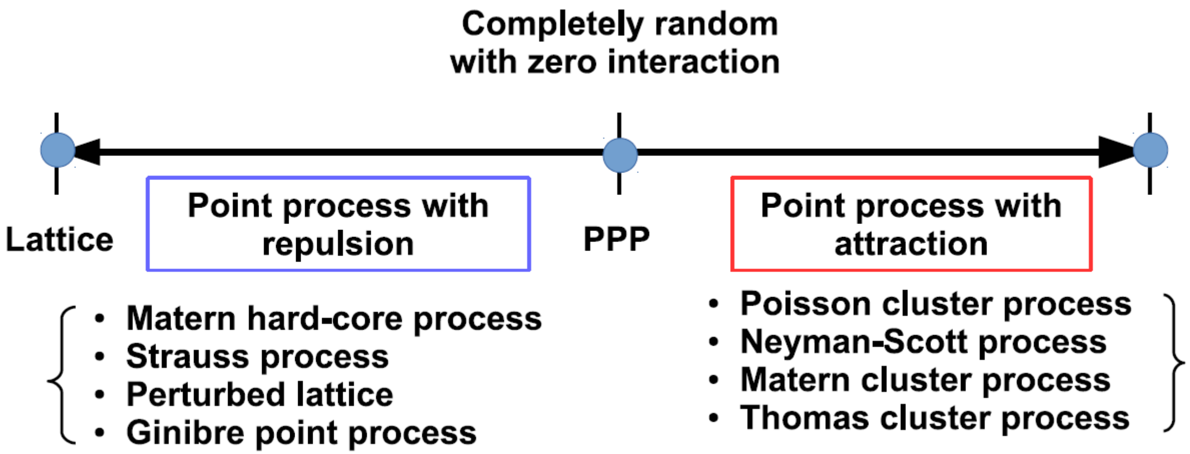
Stochastic Geometry Based Abstraction Model

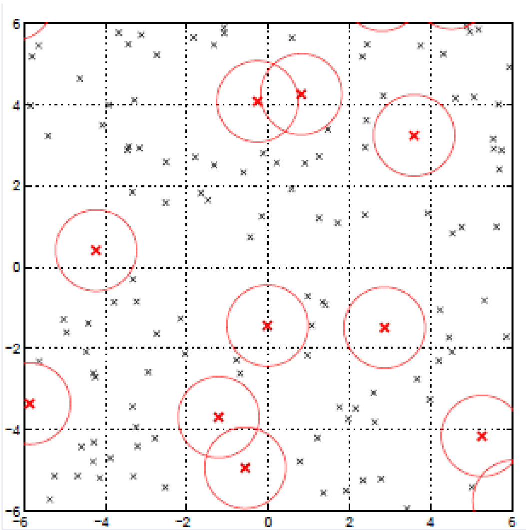
An Emerging (Tractable) Approach

- **A RANDOM SPATIAL MODEL for Heterogeneous Cellular Networks (HetNets):**
  - **K-tier network with BS locations modeled as independent marked Poisson Point Processes (PPPs)**
  - **The PPP model is surprisingly good for 1-tier as well (macro BSs): lower/upper bound to reality and trends still hold**
  - **The PPP model makes even more sense for HetNets due to less regular BSs placements for lower tiers (femto, etc.)**

Stochastic Geometry
emerges as a powerful tool for the
analysis, design and optimization
of ultra-dense HetNets

Beyond the PPP: Possible, but Math is More Complicated





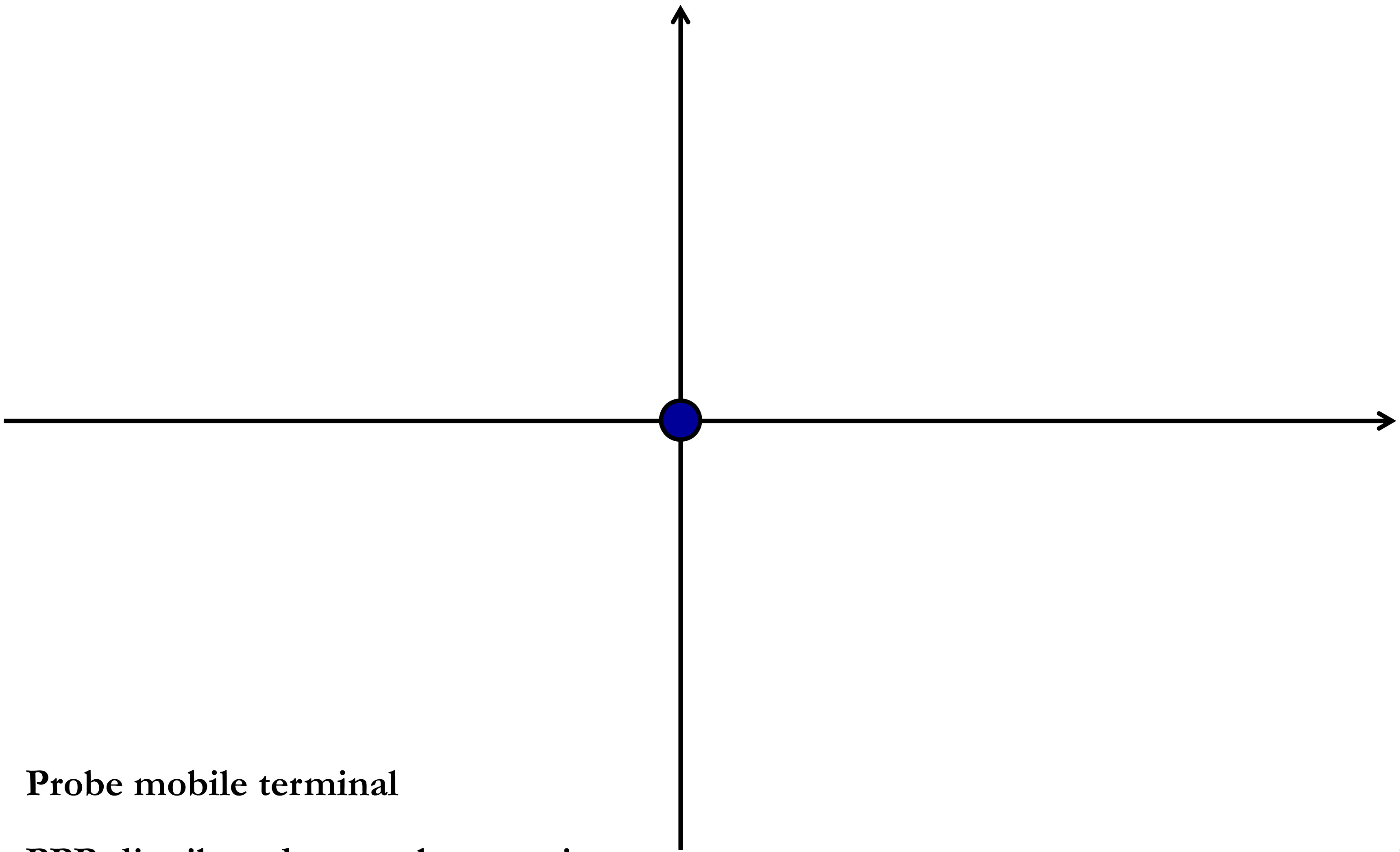
Matern Hard-Core PP

Take a homogeneous PPP and remove any pairs of points that are closer to each other than a predefined minimum distance R

Y. J. Chun, M. O. Hasna, A. Ghrayeb, and M. Di Renzo, "On modeling heterogeneous wireless networks using non-Poisson point processes", IEEE Commun. Mag., submitted. [Online]. Available: http://arxiv.org/pdf/1506.06296.pdf.

PPP-based Abstraction

How It Works (Downlink – 1-tier)

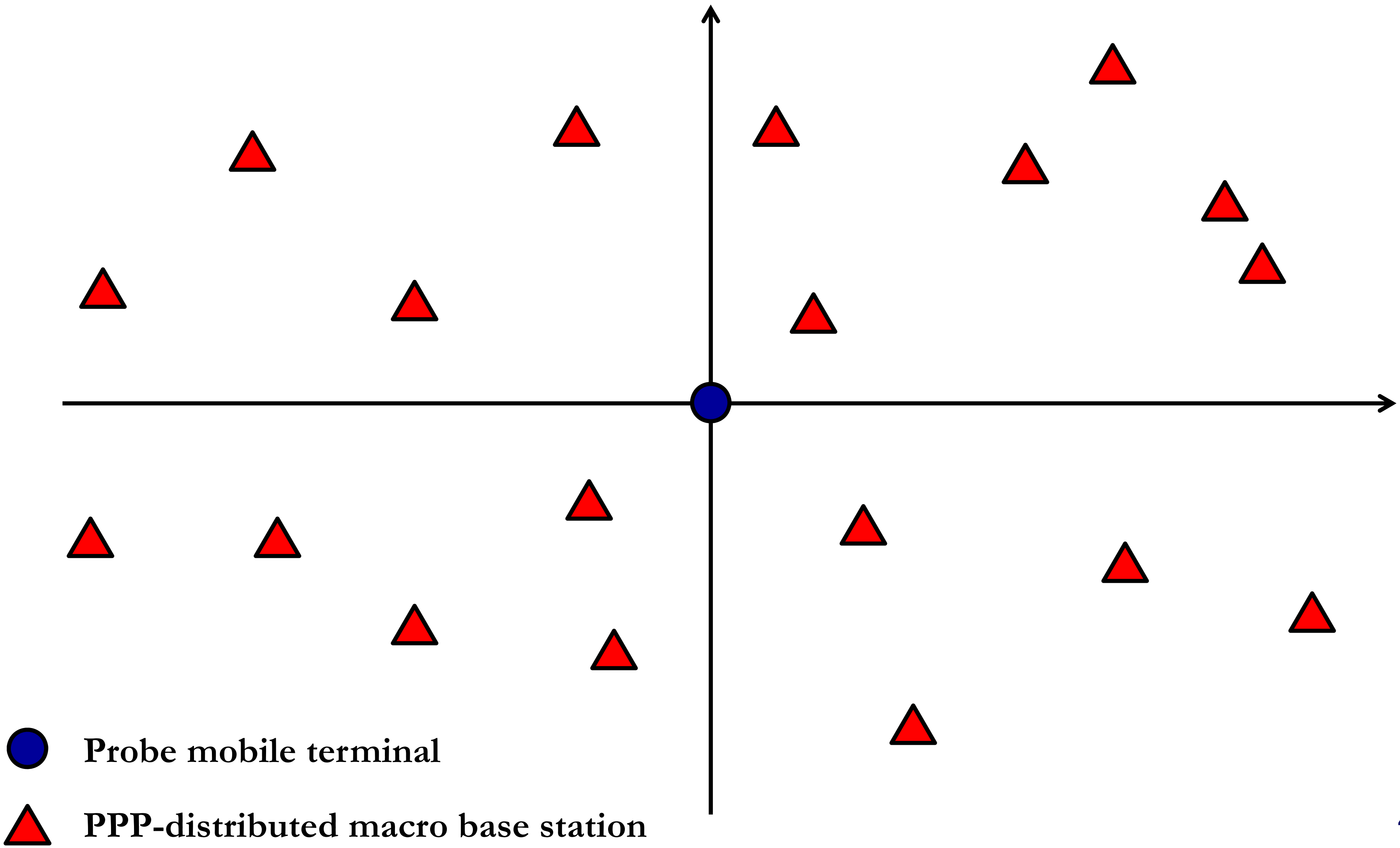


Probe mobile terminal

PPP-distributed macro base station

PPP-based Abstraction

How It Works (Downlink – 1-tier)

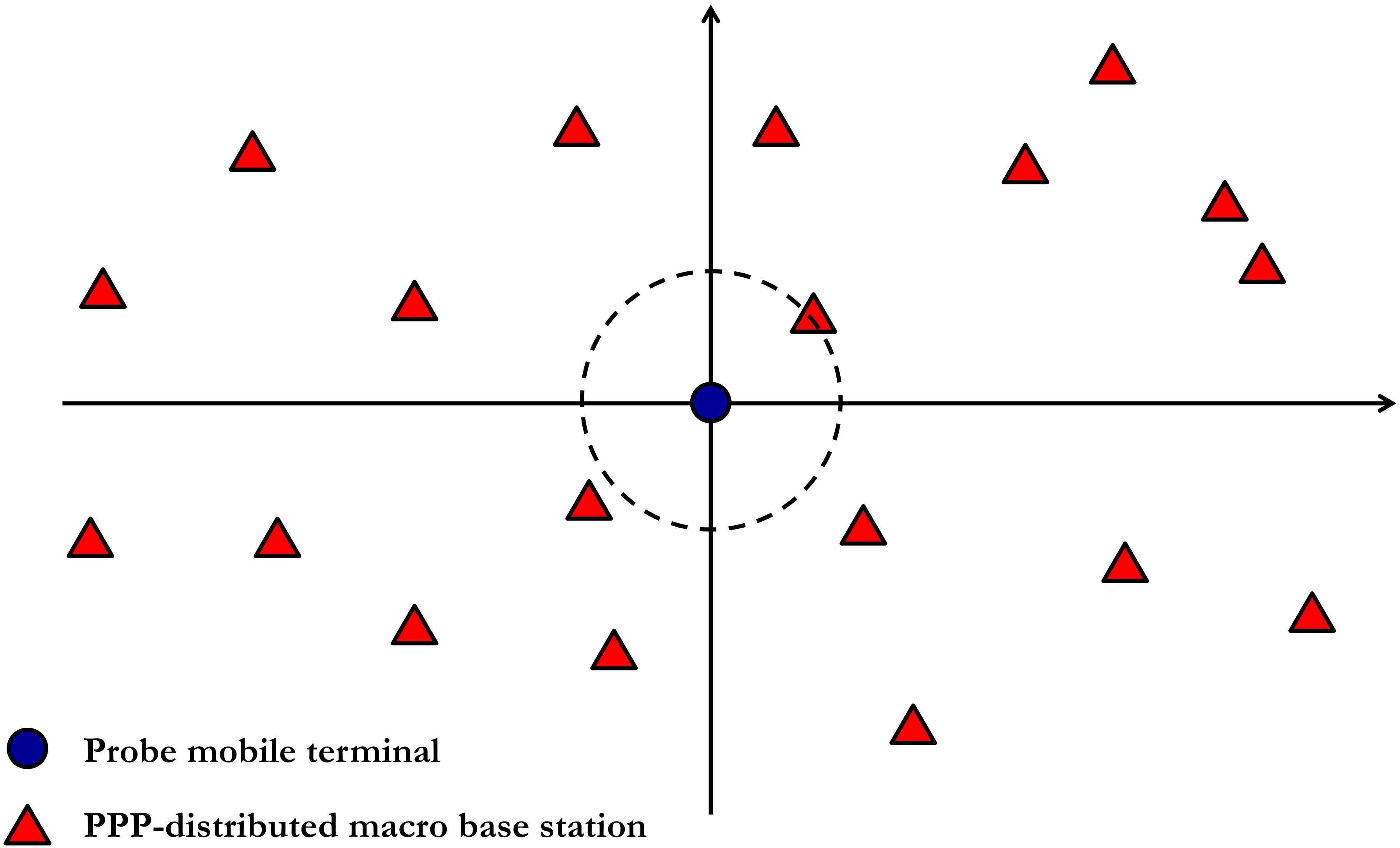


Probe mobile terminal

PPP-distributed macro base station

PPP-based Abstraction

How It Works (Downlink – 1-tier)



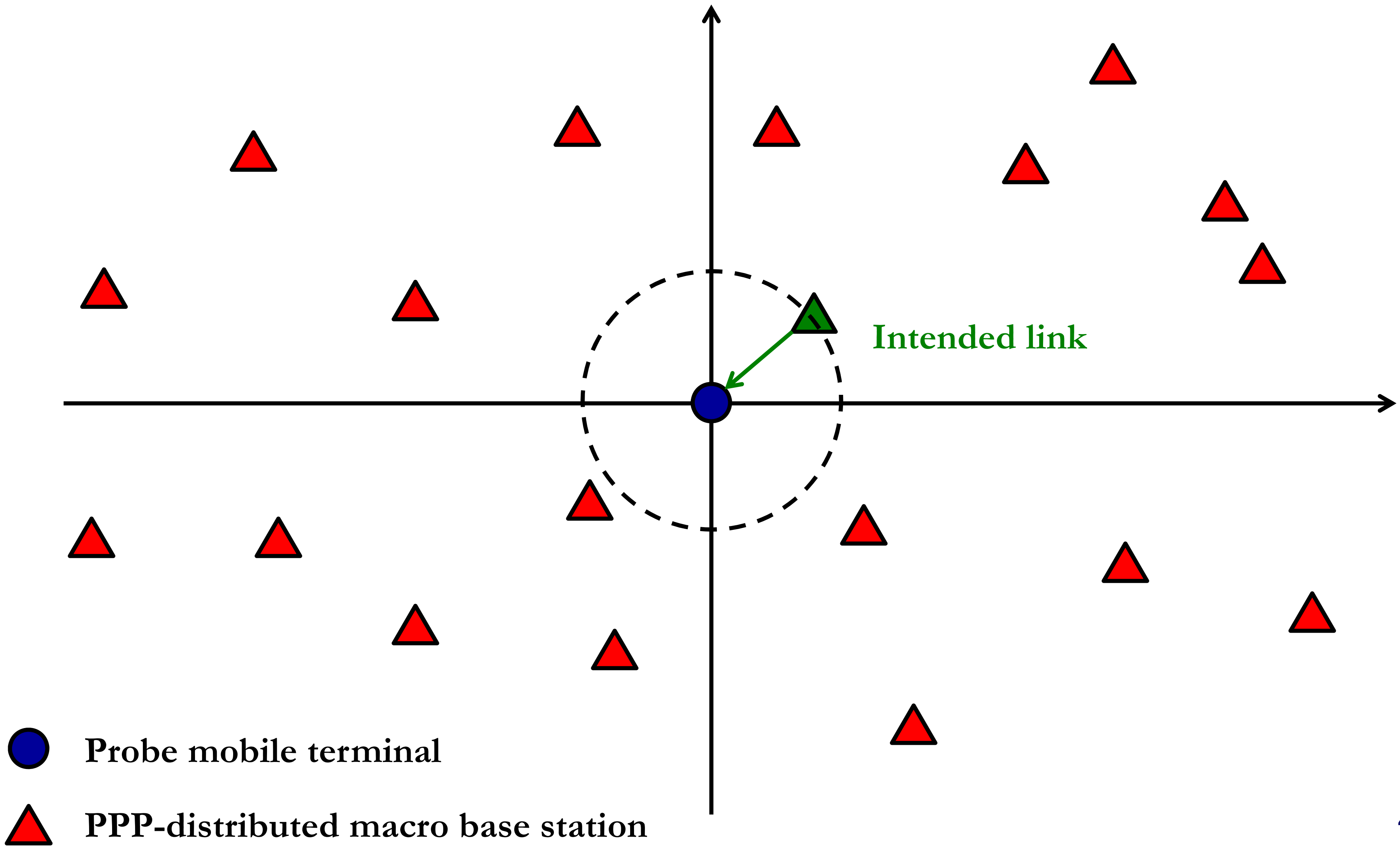
Probe mobile terminal

PPP-distributed macro base station

PPP-based Abstraction

$$C\left(r_0^{(1)},\left\{r_i^{(1)}\right\}\right)=\mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(1)},\left\{r_i^{(1)}\right\}\right)\right)$$

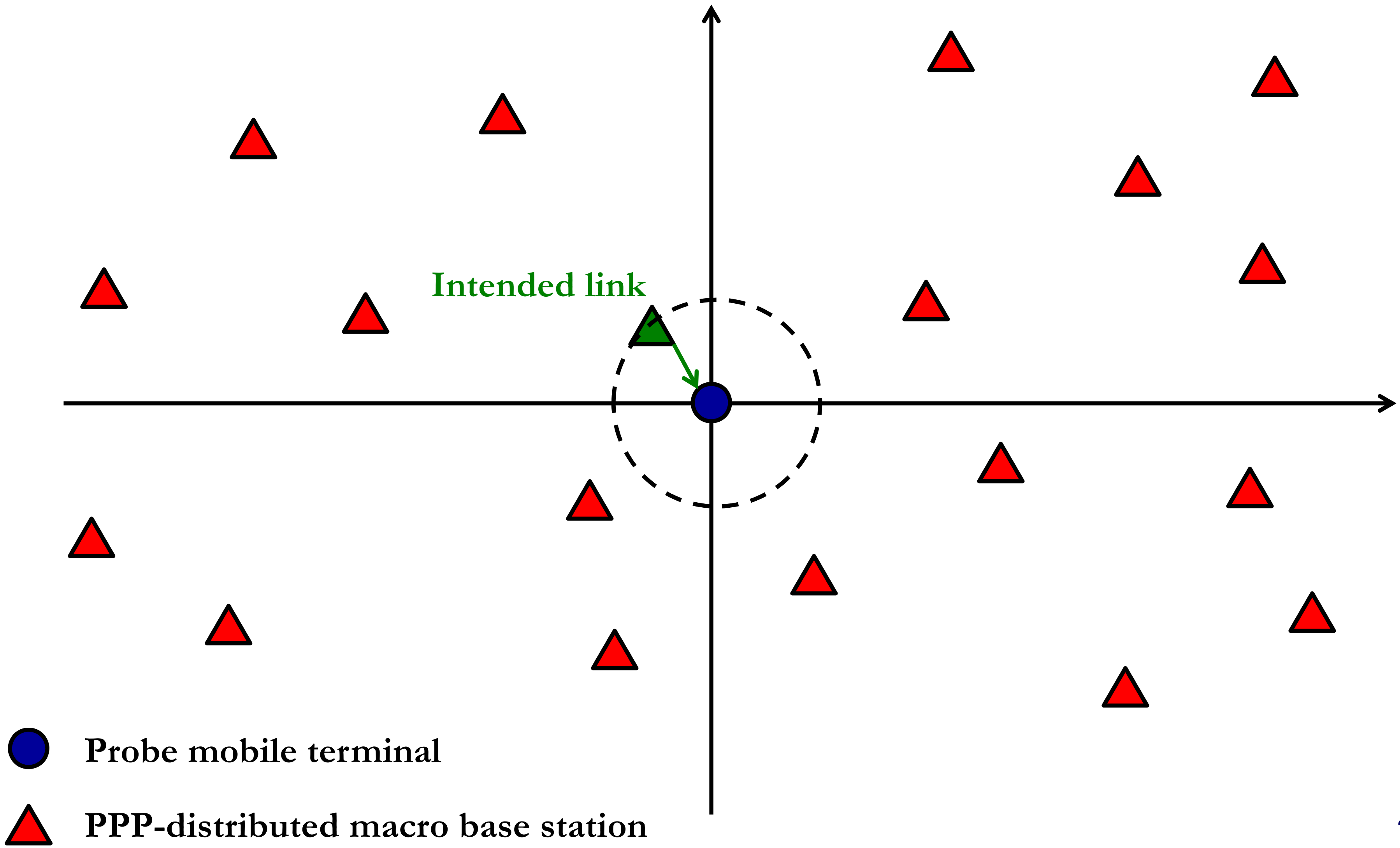
How It Works (Downlink – 1-tier)



PPP-based Abstraction

$$C\left(r_0^{(2)},\left\{r_i^{(2)}\right\}\right)=\mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(2)},\left\{r_i^{(2)}\right\}\right)\right)$$

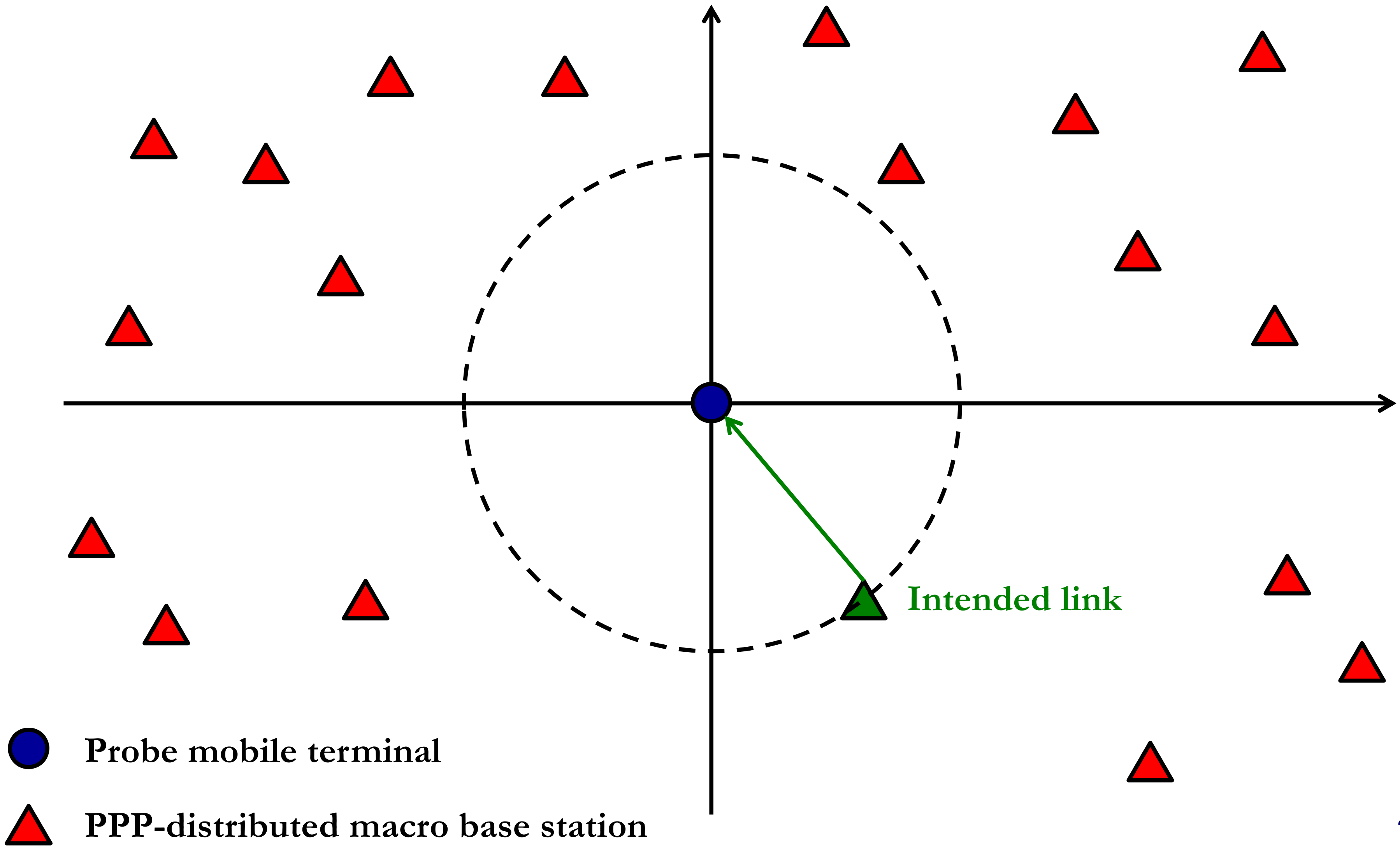
How It Works (Downlink – 1-tier)



PPP-based Abstraction

$$C\left(r_0^{(3)},\left\{r_i^{(3)}\right\}\right)=\mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(3)},\left\{r_i^{(3)}\right\}\right)\right)$$

How It Works (Downlink – 1-tier)



PPP-based Abstraction

$$\bar{C} = \mathrm{E}_{r_0,\{r_i\}}\left\{C\left(r_0,\left\{r_i\right\}\right)\right\} \approx \frac{1}{N}\sum_{n=1}^{N} C\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)$$

$$= \frac{1}{N}\sum_{n=1}^{N} \mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)\right)$$

PPP-based Abstraction

$$\bar{C} = \mathrm{E}_{r_0,\{r_i\}}\left\{C\left(r_0,\{r_i\}\right)\right\} \approx \frac{1}{N}\sum_{n=1}^{N} C\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)$$

$$= \frac{1}{N}\sum_{n=1}^{N} \mathrm{B_w}\log_2\left(1+\mathrm{SINR}\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)\right)$$

Are you kidding me? … What makes it different?

PPP-based Abstraction

$$\bar{C} = \mathrm{E}_{r_0,\{r_i\}}\left\{C\left(r_0,\{r_i\}\right)\right\} \approx \frac{1}{N}\sum_{n=1}^{N} C\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)$$

$$= \frac{1}{N}\sum_{n=1}^{N} \mathrm{B_w} \log_2\left(1+\mathrm{SINR}\left(r_0^{(n)},\left\{r_i^{(n)}\right\}\right)\right)$$

Are you kidding me? … What makes it different?

The answer:

…this spatial expectation

can **be computed mathematically…**

… On Abstraction Modeling …

George Edward Pelham Box
(18 October 1919 – 28 March 2013)
Statistician
Fellow of the Royal Society (UK)
Director of the Statistical Research Group
(Princeton University)
Emeritus Professor
(University of Wisconsin-Madison)

"…all models are wrong, but some are useful…"

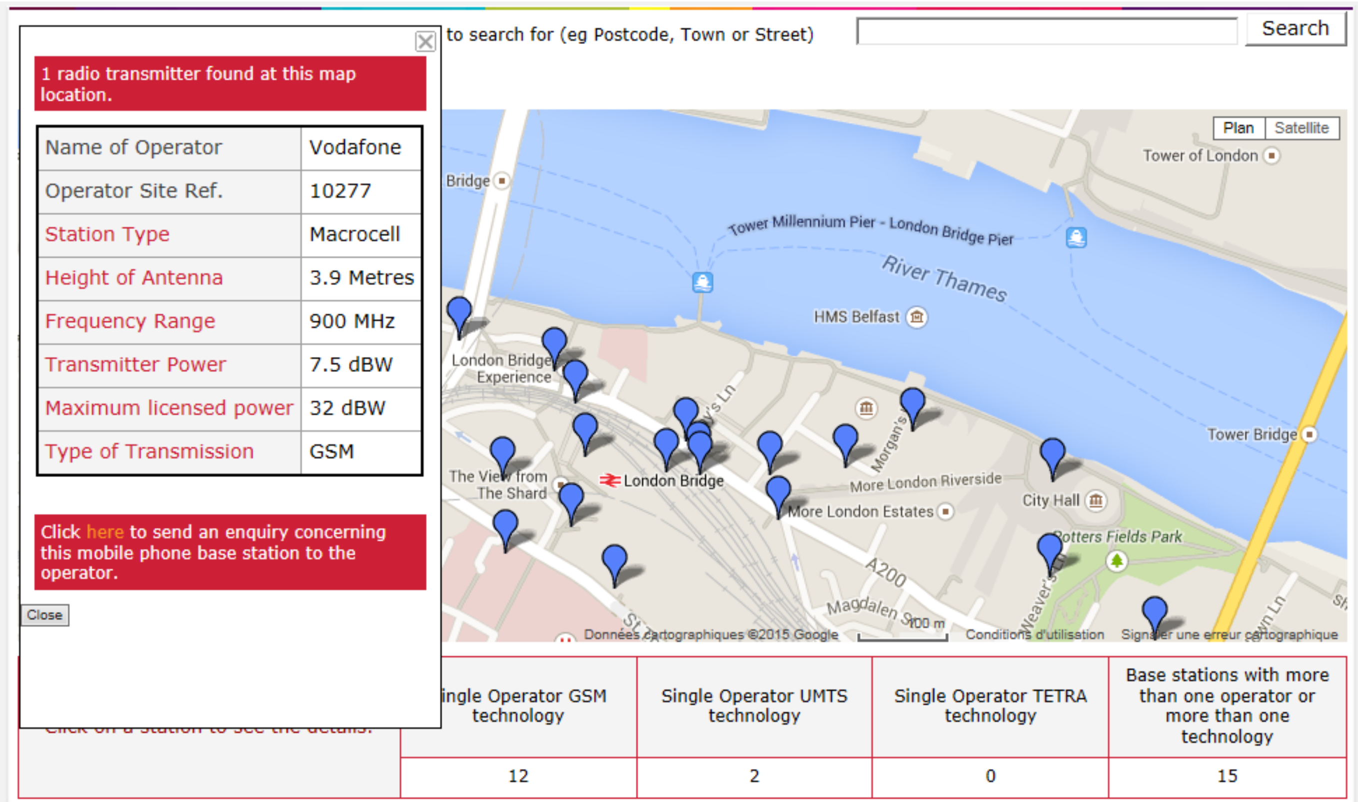
Is This Abstraction Model Accurate?

- **Methodology:**

Is This Abstraction Model Accurate?

- **Methodology:**
  - **Actual base station locations from OFCOM (UK)**

OFCOM: London "London Bridge area"

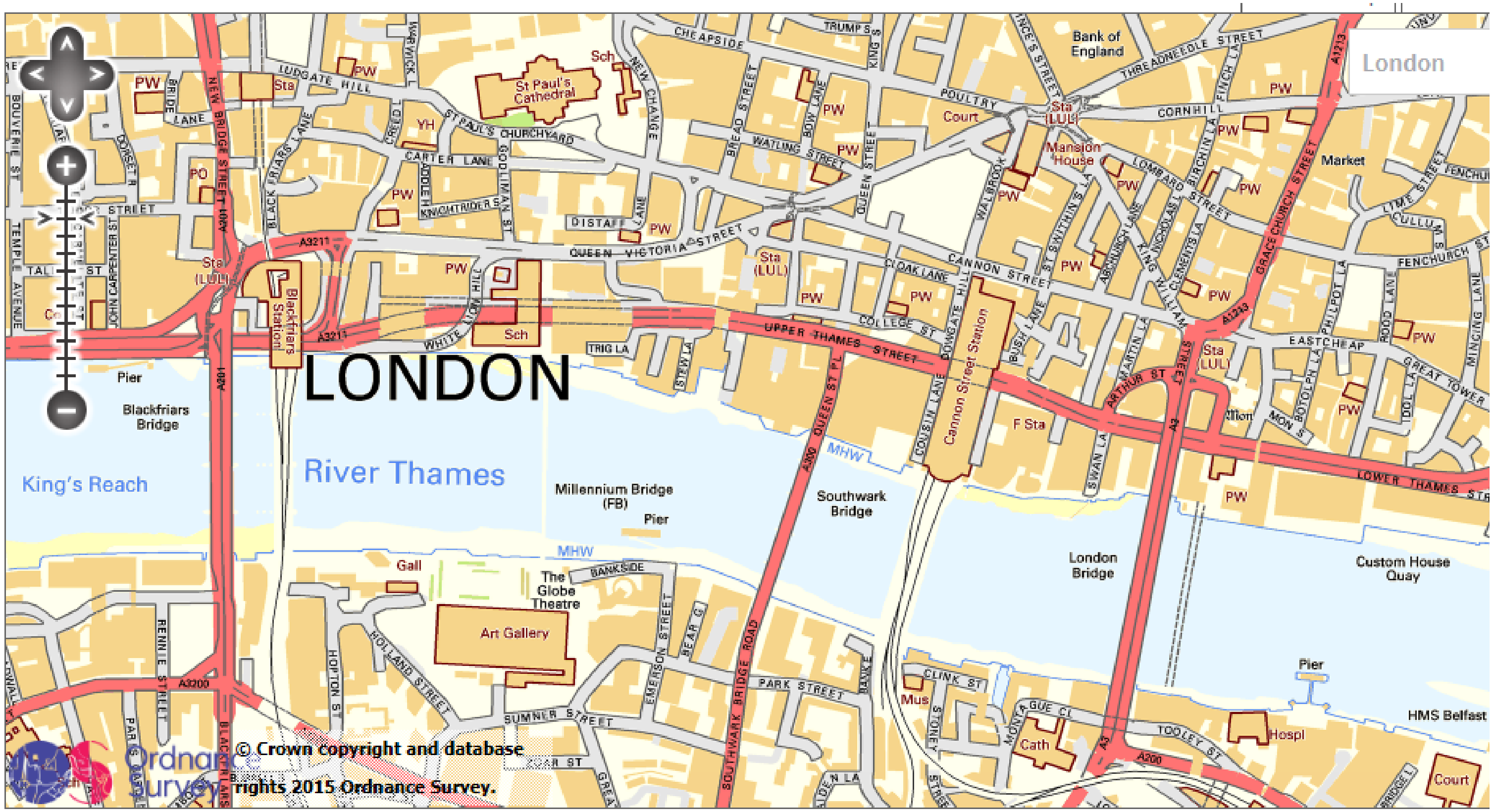


OFCOM: http://stakeholders.ofcom.org.uk/sitefinder/sitefinder-dataset/

Is This Abstraction Model Accurate?

- **Methodology:**
  - Actual base station locations from **OFCOM** (UK)
  - Actual building footprints from **ORDNANCE SURVEY** (UK)

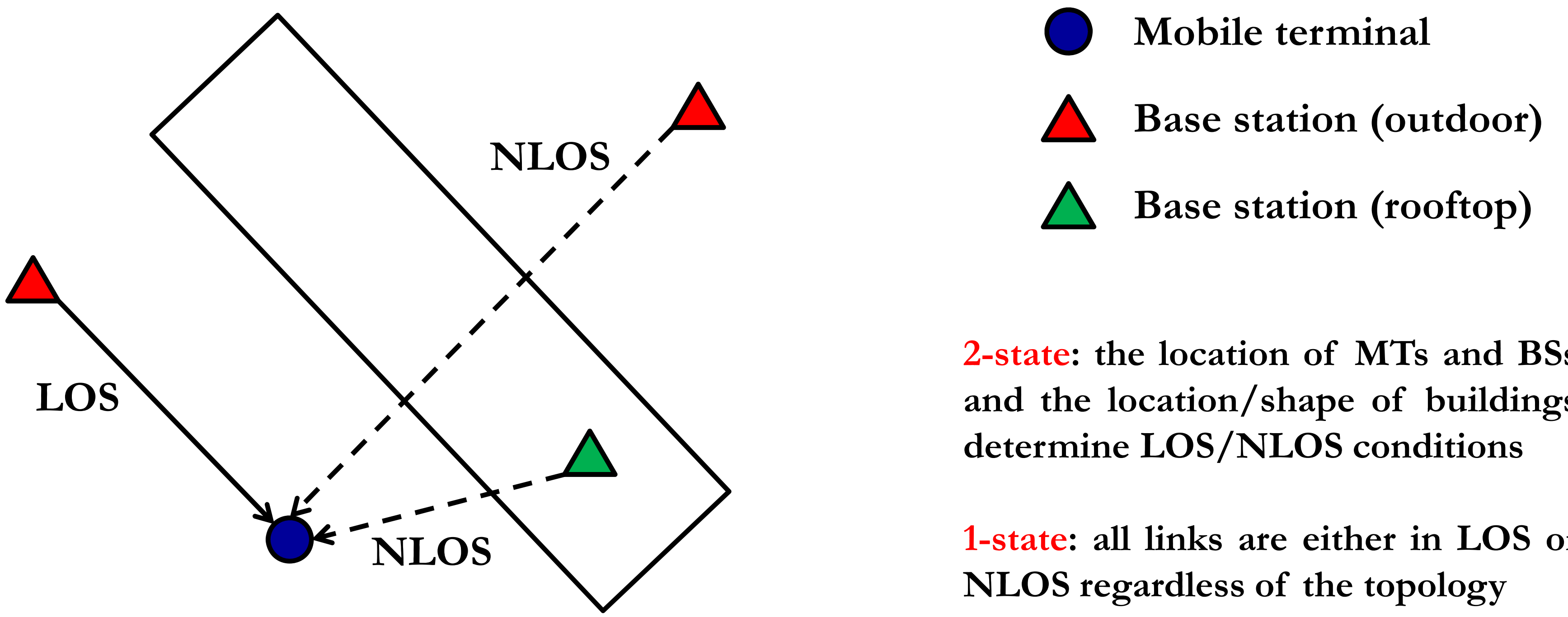
ORDNANCE SURVEY: London "London Bridge area"



OFCOM: http://stakeholders.ofcom.org.uk/sitefinder/sitefinder-dataset/
ORDNANCE SURVEY: https://www.ordnancesurvey.co.uk/opendatadownload/products.html

Is This Abstraction Model Accurate?

- **Methodology:**
  - **Actual base station locations from OFCOM (UK)**
  - **Actual building footprints from ORDNANCE SURVEY (UK)**
  - **Channel model added on top (1-state and 2-state with LOS/NLOS)**



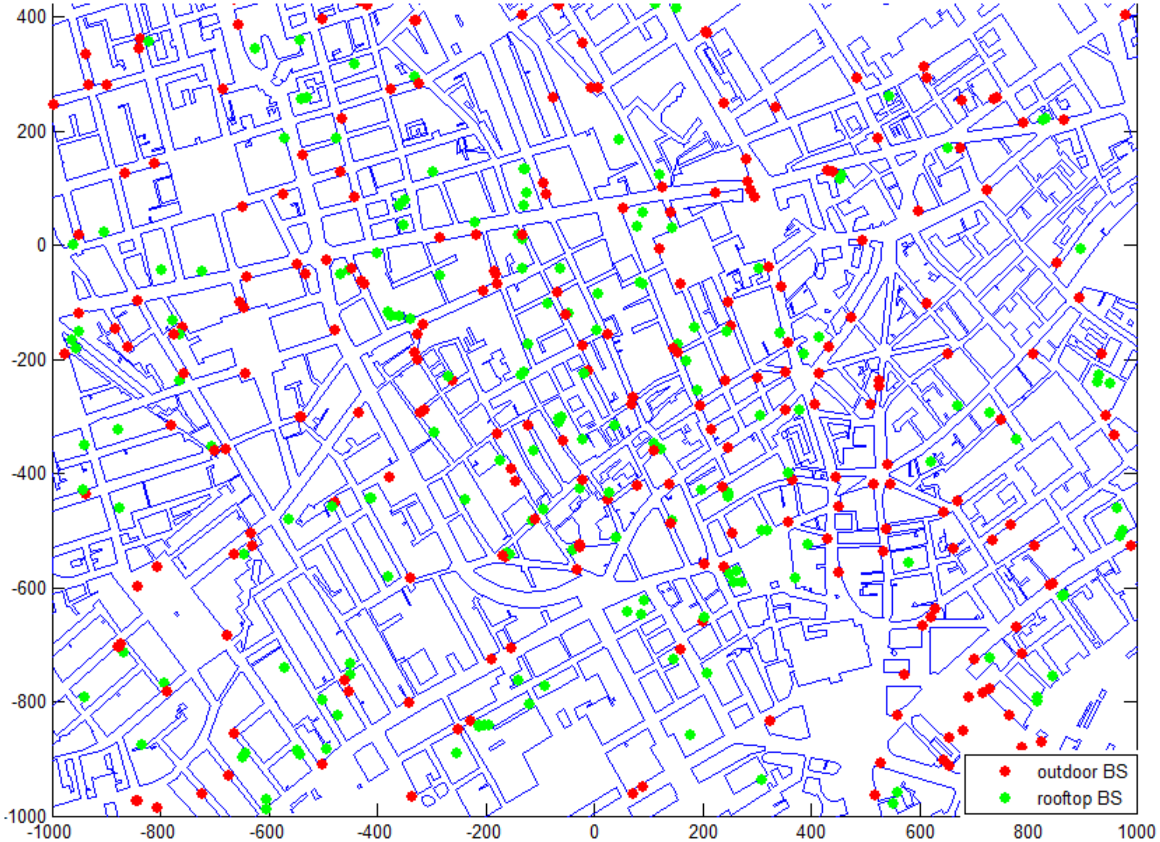
2-state: the location of MTs and BSs and the location/shape of buildings determine LOS/NLOS conditions

1-state: all links are either in LOS or NLOS regardless of the topology

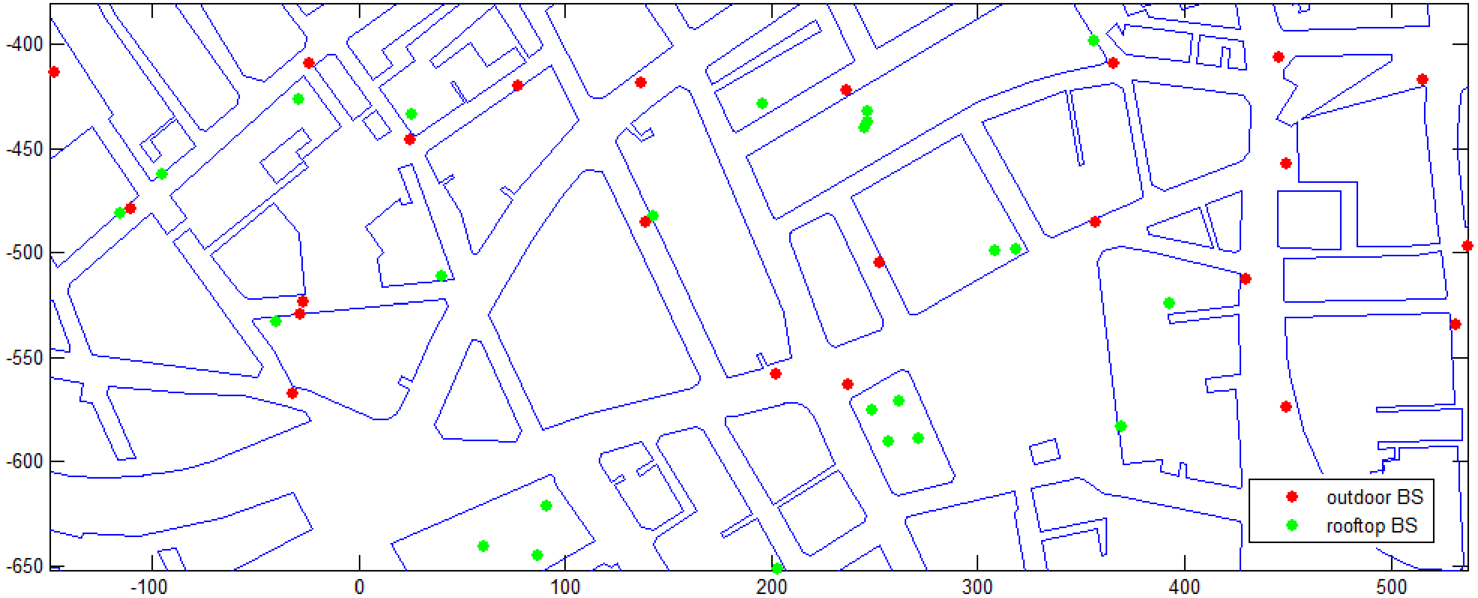
OFCOM: http://stakeholders.ofcom.org.uk/sitefinder/sitefinder-dataset/
ORDNANCE SURVEY: https://www.ordnancesurvey.co.uk/opendatadownload/products.html

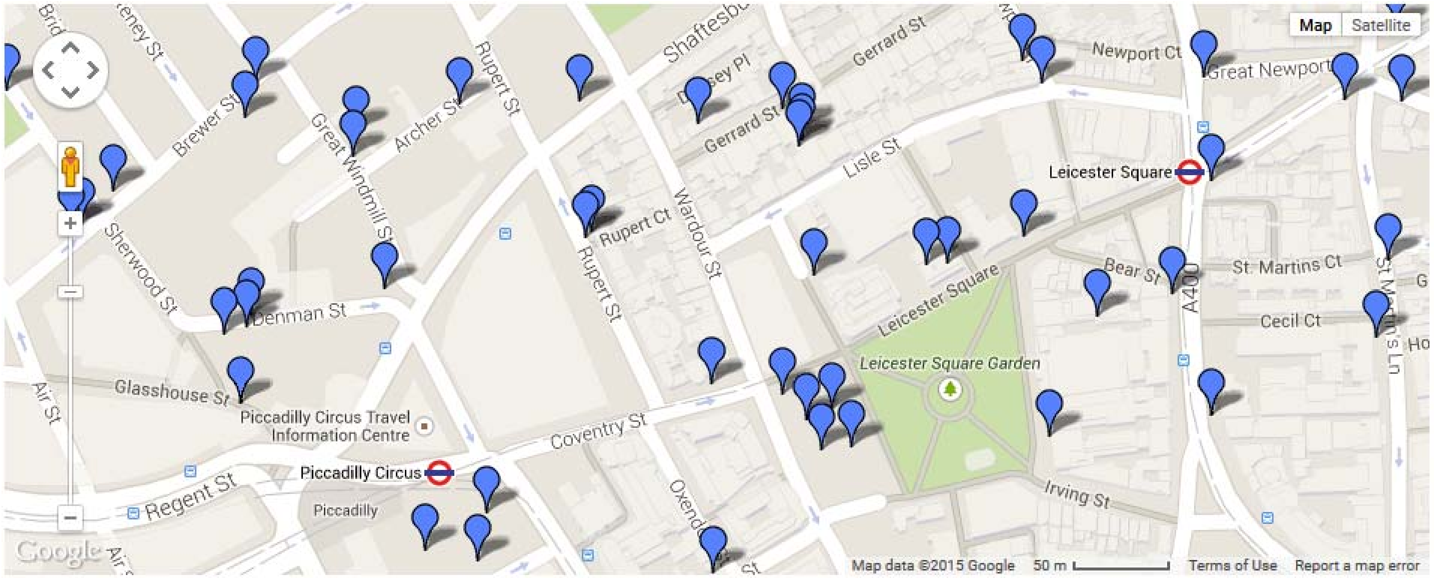
The London Case Study (1/7)

	O2 + Vodafone	O2	Vodafone
Number of BSs	319	183	136
Number of rooftop BSs	95	62	33
Number of outdoor BSs	224	121	103
Average cell radius (m)	63.1771	83.4122	96.7577

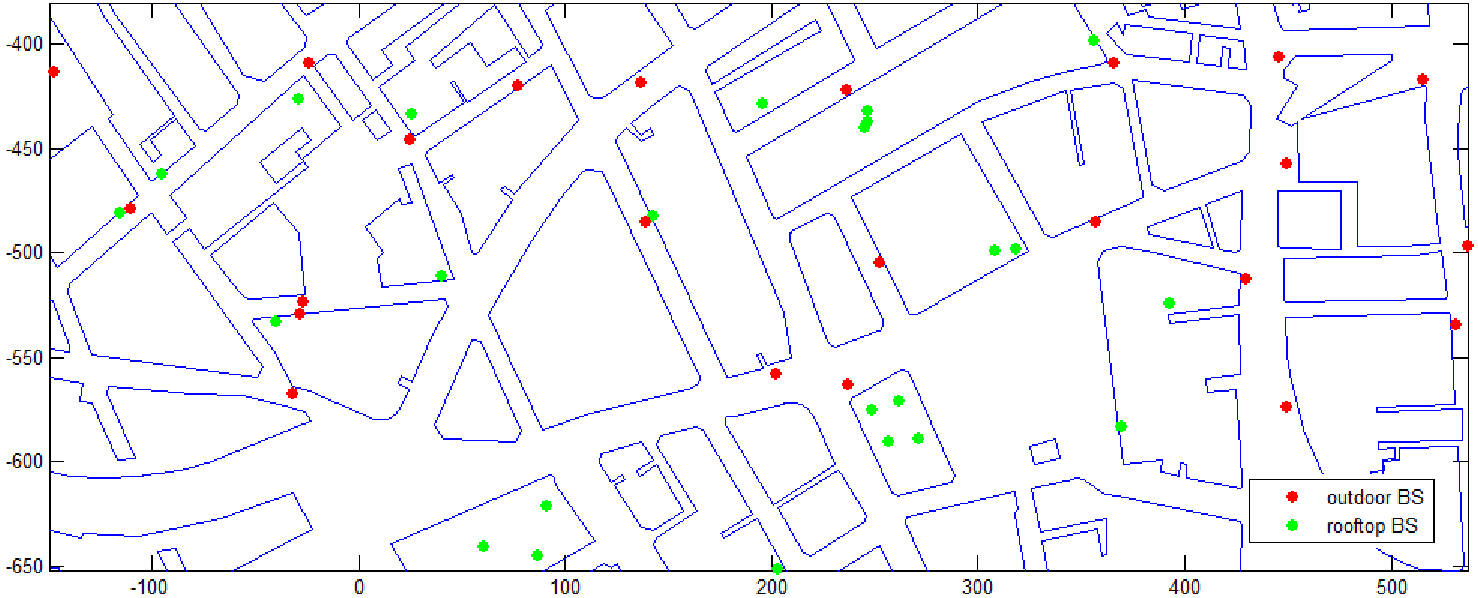


The London Case Study (2/7)





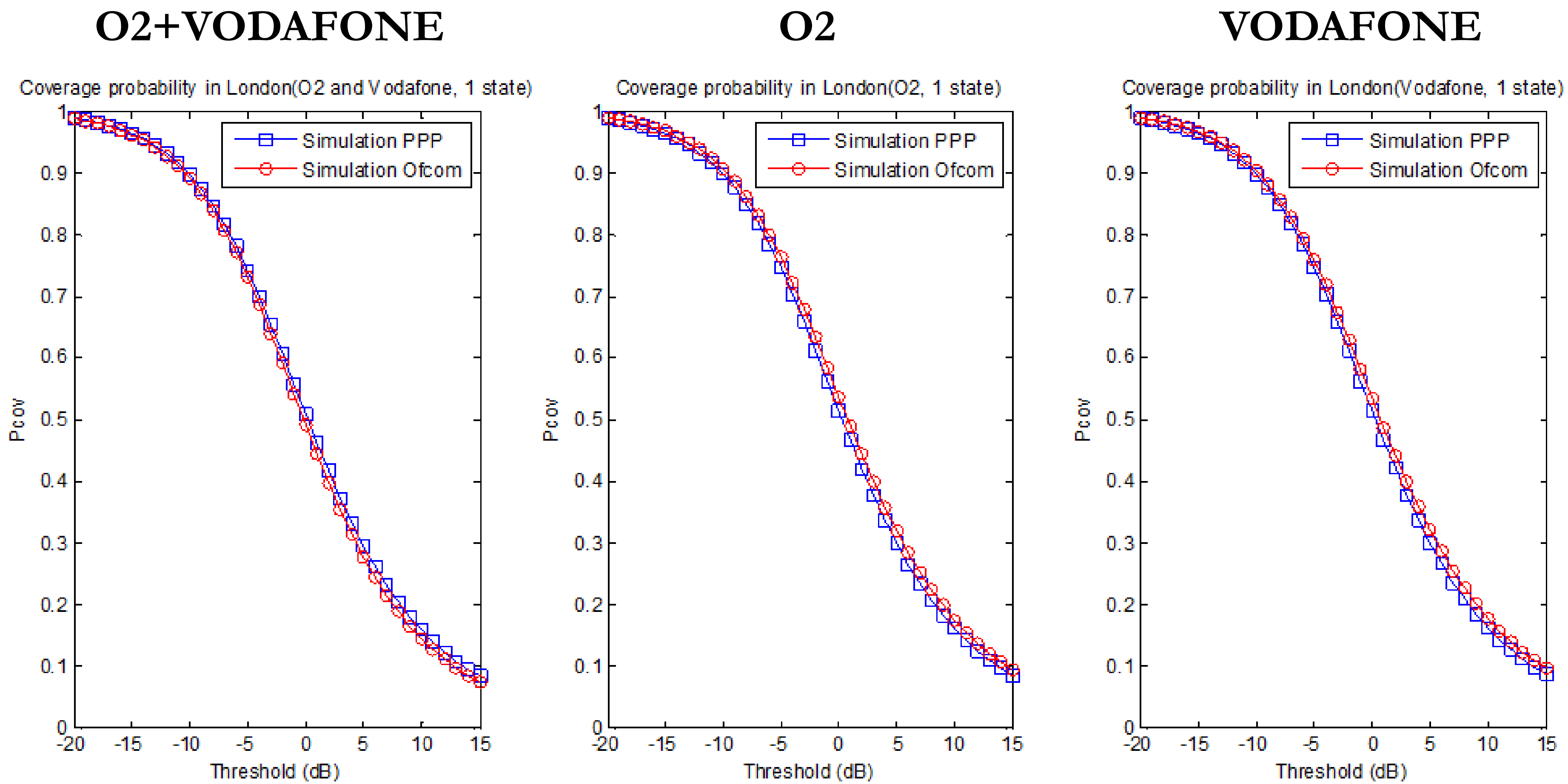
The London Case Study (3/7)



The London Case Study (4/7)

PPP Accuracy: 1-State Channel Model

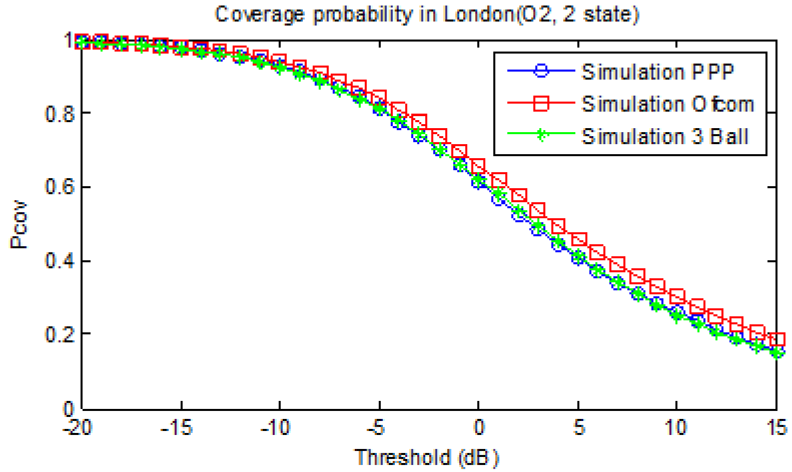
- **OFCOM: Actual base station locations, (actual building footprints), actual channels**
- **PPP: Random base station locations, (actual building footprints), actual channels**



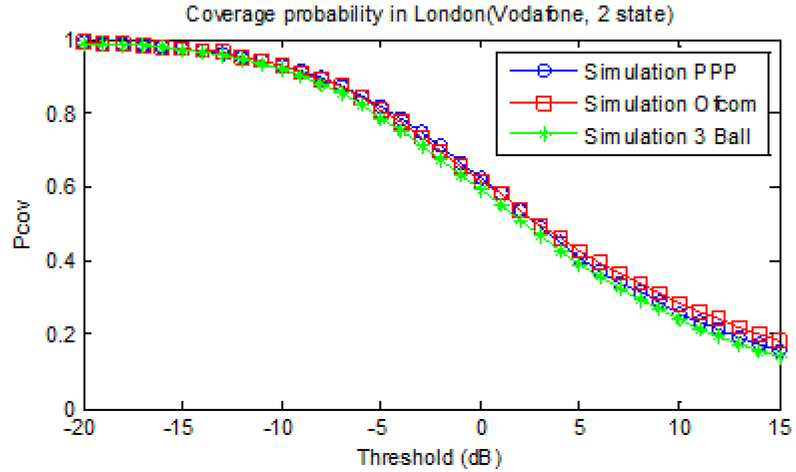
The London Case Study (5/7)

PPP Accuracy: 2-State Channel Model

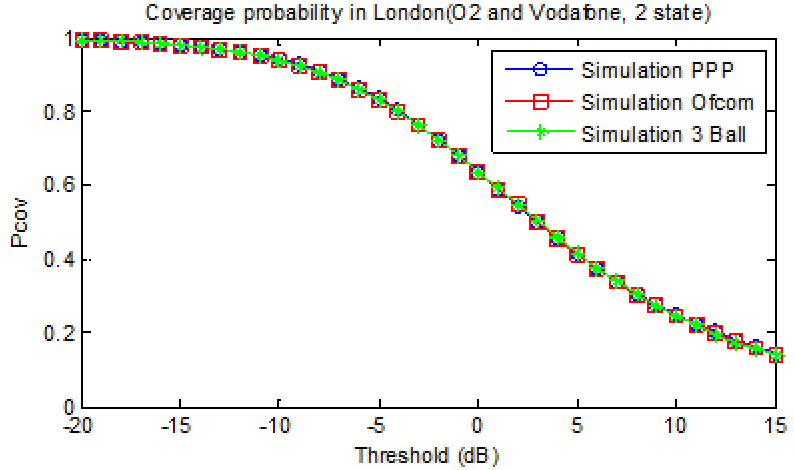
O2



VODAFONE

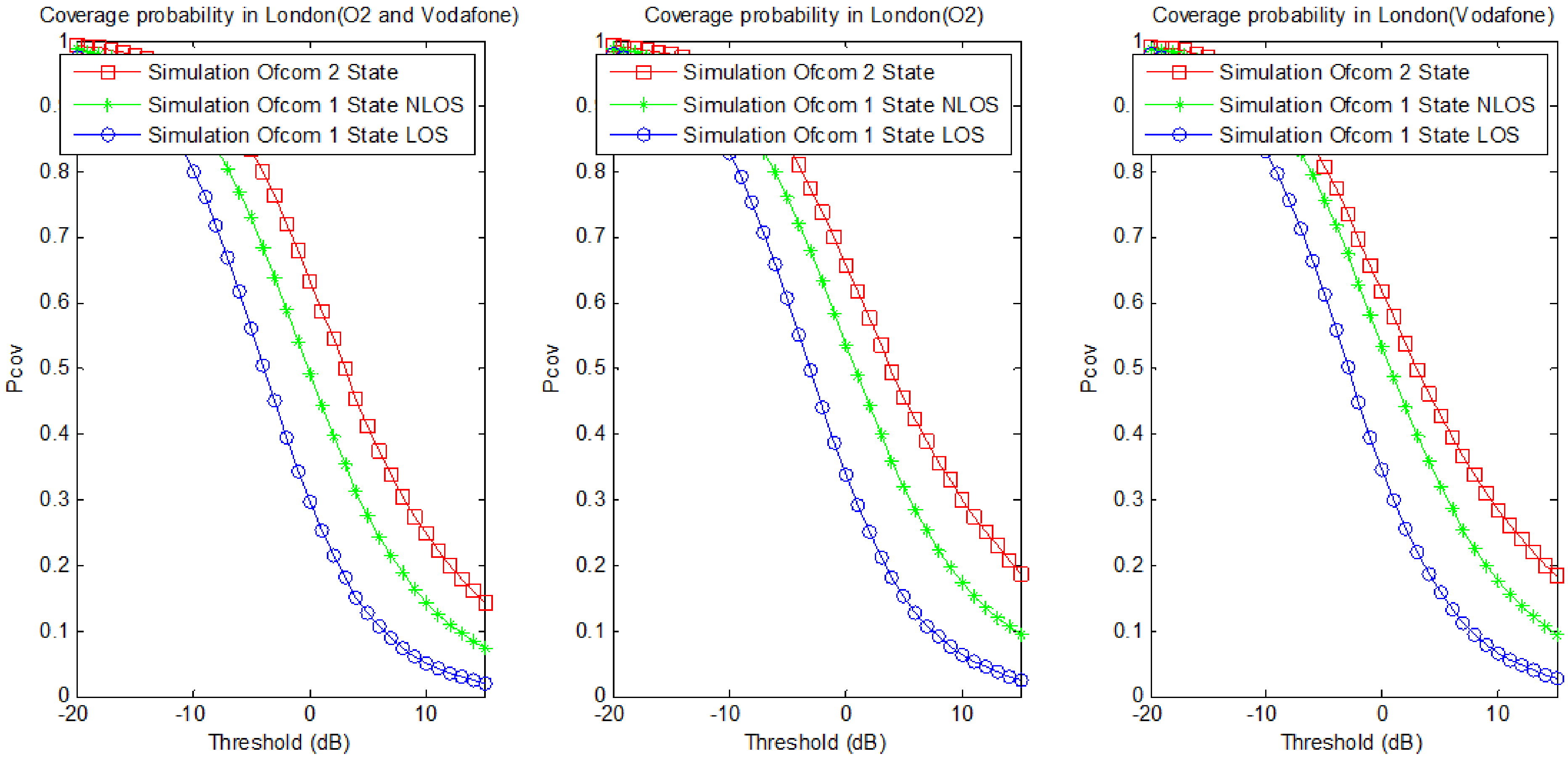


O2+VODAFONE



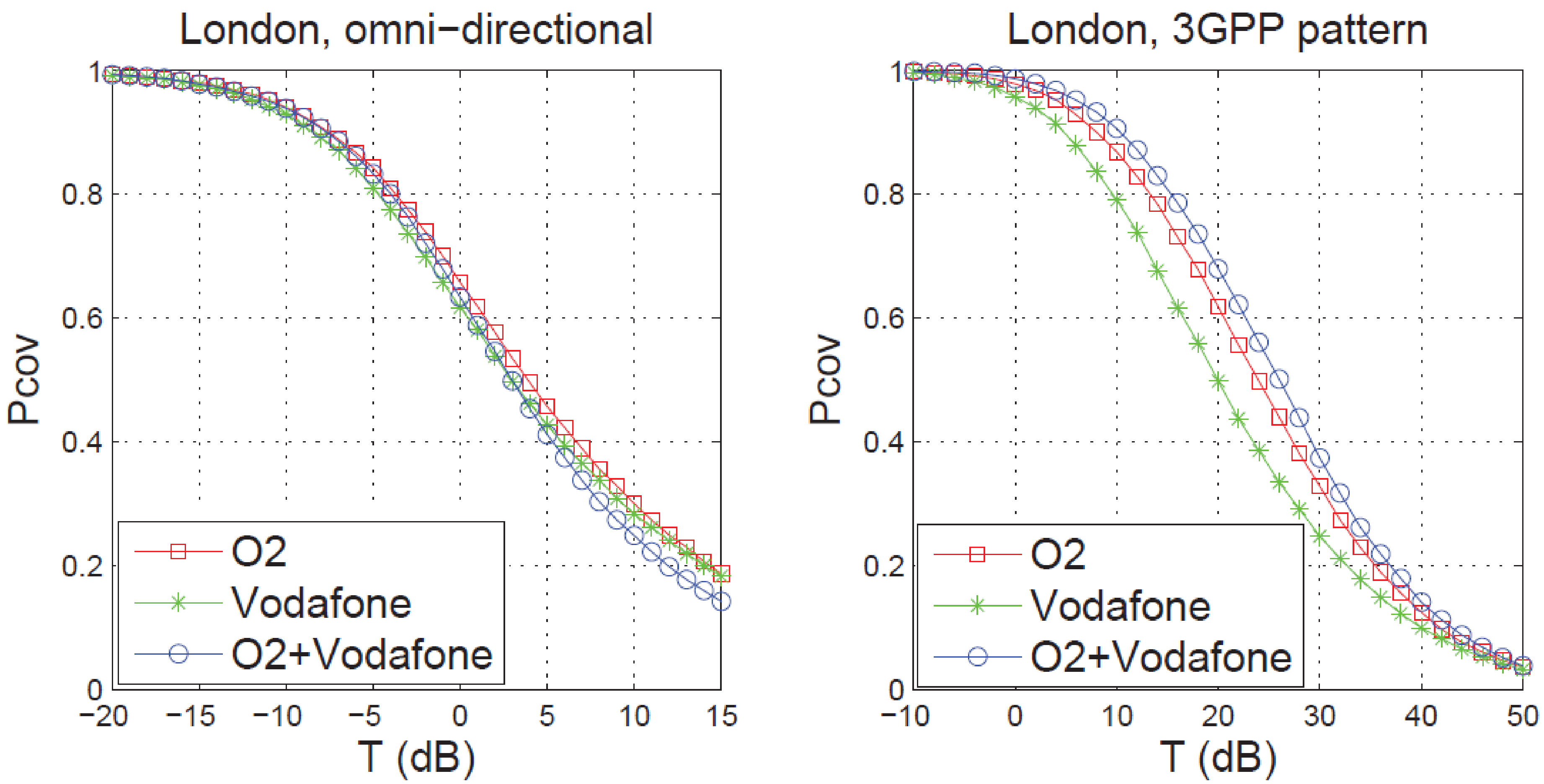
The London Case Study (6/7)

- 1-State vs. 2-State Channel Models:
  - Only LOS → Worse coverage, as interference is enhanced
  - Only NLOS → In-between, as interference is reduced but probe link gets worse
  - LOS and NLOS → More realistic: we can model it with stochastic geometry



The London Case Study (7/7)

Omni-Directional vs. 3GPP Radiation Patterns



Why Is This Modeling Approach So Accurate?

	O2 + Vodafone	O2	Vodafone
Number of BSs	319	183	136
Number of rooftop BSs	95	62	33
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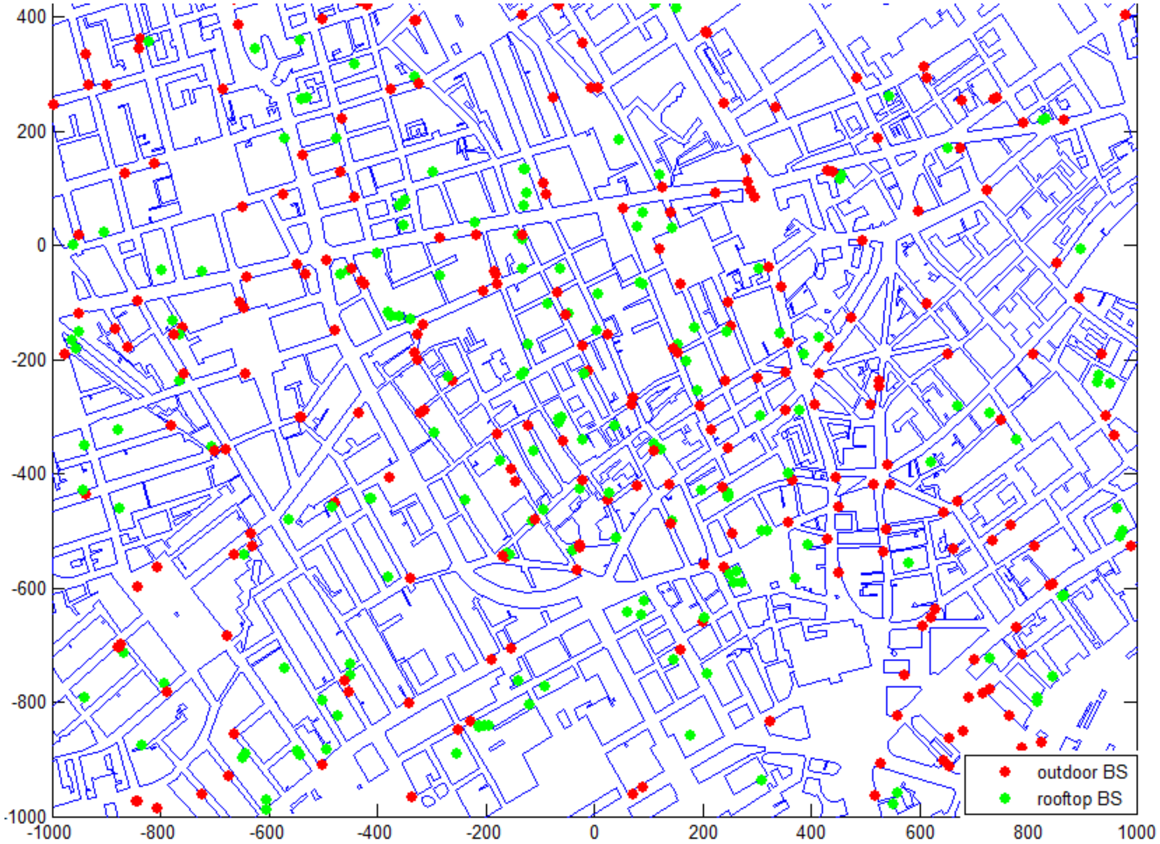
Average cell radius (m)	63.1771	83.4122	96.7577



Intrigued Enough?

… Further Information and Case Studies …

Stochastic Geometry Modeling of Cellular Networks: Analysis, Simulation and Experimental Validation

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ABSTRACT

Due to the increasing heterogeneity and deployment density of emerging cellular networks, new flexible and scalable approaches for their modeling, simulation, analysis and optimization are needed. Recently, a new approach has been proposed: it is based on the theory of point processes and it leverages tools from stochastic geometry for tractable system-level modeling, performance evaluation and optimization. In this paper, we investigate the accuracy of this emerging abstraction for modeling cellular networks, by explicitly taking realistic base station locations, building footprints, spatial blockages and antenna radiation patterns into account. More specifically, the base station locations and the building footprints are taken from two publicly available databases from the United Kingdom. Our study confirms that the abstraction model based on stochastic geometry is capable of accurately modeling the communication performance of cellular networks in dense urban environments.

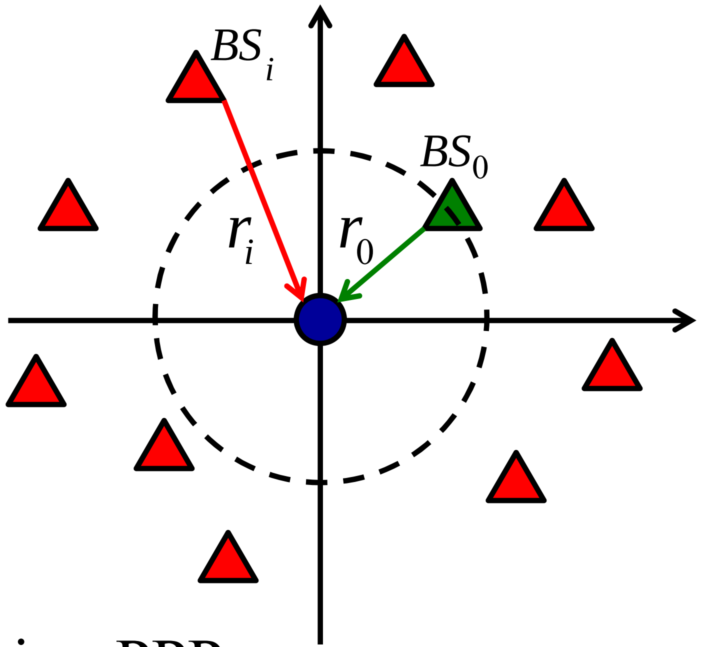
pected to provide [1]. Modeling, simulating, analyzing and optimizing such networks is, however, a non-trivial problem. This is due to the large number of access points that are expected to be deployed and their dissimilar characteristics, which encompass deployment density, transmit power, access technology, etc. Motivated by these considerations, several researchers are investigating different options for modeling, simulating, mathematically analyzing and optimizing these networks. The general consensus is, in fact, that the methods used in the past for modeling cellular networks, e.g., the hexagonal grid-based model [2], are not sufficiently scalable and flexible for taking the ultra-dense and irregular deployments of emerging cellular topologies into account.

Recently, a new approach for overcoming these limitations has been proposed. It is based on the theory of point processes (PP) and leverages tools from stochastic geometry for system-level modeling, performance evaluation and optimization of cellular networks [3]. In this paper, it is referred

W. Lu and M. Di Renzo, "Stochastic Geometry Modeling of Cellular Networks: Analysis, Simulation and Experimental Validation", ACM Int. Conf. Modeling, Analysis and Simulation of Wireless and Mobile Systems, Nov. 2015. [Online]. Available: http://arxiv.org/pdf/1506.03857.pdf.

How It Works: The Magic of Stochastic Geometry (1/5)

… understanding the basic math …



Φ is a PPP

$$\mathrm{P}_{\mathrm{cov}} = \Pr\left\{ \mathrm{SINR} > T \right\}$$

$$\mathrm{SINR} = \frac{P\left|h_o\right|^2 r_o^{-\alpha}}{\sigma^2 + I_{agg}\left(r_0\right)}$$

$$I_{agg}\left(r_0\right) = \sum_{i \in \Phi \setminus BS_0} P\left|h_i\right|^2 r_i^{-\alpha}$$

$$\mathrm{P}_{\mathrm{cov}} = \Pr\left\{ \frac{P\left|h_o\right|^2 r_o^{-\alpha}}{\sigma^2 + I_{agg}\left(r_0\right)} > T \right\} = \ldots$$

How It Works: The Magic of Stochastic Geometry (2/5)

… understanding the basic math …

$$\mathrm{P}_{\mathrm{cov}} = \Pr\left\{ \frac{P\left|h_o\right|^2 r_o^{-\alpha}}{\sigma^2 + I_{agg}\left(r_0\right)} > T \right\}$$

$$= \Pr\left\{ \left|h_o\right|^2 > \left(\sigma^2 + I_{agg}\left(r_0\right)\right) P^{-1} T r_o^{\alpha} \right\}$$

$$\left(\left|h_o\right|^2 \sim \exp \Rightarrow \right) = \mathrm{E}_{I_{agg}\left(r_0\right), r_0} \left\{ \exp\left(-\left(\sigma^2 + I_{agg}\left(r_0\right)\right) P^{-1} T r_o^{\alpha} \right) \right\}$$

$$\begin{pmatrix} \mathrm{MGF}_X\left(s\right) = \\ \mathrm{E}_X\left\{e^{-sX}\right\} \Rightarrow \end{pmatrix} = \mathrm{E}_{r_0} \left\{ \exp\left(-\sigma^2 P^{-1} T r_o^{\alpha} \right) \mathrm{MGF}_{I_{agg}\left(r_0\right)}\left(P^{-1} T r_o^{\alpha} \right) \right\}$$

How It Works: The Magic of Stochastic Geometry (3/5)

… understanding the basic math …

$$\mathrm{P}_{\mathrm{cov}} = \mathrm{E}_{r_0}\left\{\exp\left(-T\sigma^2 P^{-1} r_o^{\alpha}\right)\mathrm{MGF}_{I_{agg}(r_0)}\left(P^{-1}T r_o^{\alpha}\right)\right\}$$

$$= \int_0^{+\infty} \exp\left(-T\sigma^2 P^{-1}\xi^{\alpha}\right)\mathrm{MGF}_{I_{agg}(r_0)}\left(P^{-1}T\xi^{\alpha}\right)\mathrm{PDF}_{r_0}\left(\xi\right)d\xi$$

How It Works: The Magic of Stochastic Geometry (3/5)

… understanding the basic math …

$$\mathrm{P_{cov}} = \mathrm{E}_{r_0}\left\{ \exp\left(-T\sigma^2 P^{-1} r_o^{\alpha}\right) \mathrm{MGF}_{I_{agg}(r_0)}\left(P^{-1} T r_o^{\alpha}\right)\right\}$$

$$= \int_0^{+\infty} \exp\left(-T\sigma^2 P^{-1} \xi^{\alpha}\right) \mathrm{MGF}_{I_{agg}(r_0)}\left(P^{-1} T \xi^{\alpha}\right) \mathrm{PDF}_{r_0}\left(\xi\right) d\xi$$

Trivial so far… where is the magic?

How It Works: The Magic of Stochastic Geometry (3/5)

… understanding the basic math …

$$\mathrm{P}_{\mathrm{cov}} = \mathrm{E}_{r_0}\left\{\exp\left(-T\sigma^2 P^{-1} r_o^{\alpha}\right)\mathrm{MGF}_{I_{agg}(r_0)}\left(P^{-1} T r_o^{\alpha}\right)\right\}$$

$$= \int_0^{+\infty} \exp\left(-T\sigma^2 P^{-1}\xi^{\alpha}\right)\mathrm{MGF}_{I_{agg}(r_0)}\left(P^{-1} T \xi^{\alpha}\right)\mathrm{PDF}_{r_0}(\xi)\, d\xi$$

Trivial so far… where is the magic?

Stochastic Geometry provides us with the mathematical tools for computing, in closed-form, the MGF and the PDF of the equation above

How It Works: The Magic of Stochastic Geometry (4/5)

… understanding the basic math …

$$I_{agg}\left(r_0\right) = \sum_{i \in \Phi \backslash BS_0} P\left|h_i\right|^2 r_i^{-\alpha}$$

The aggregate other-cell interference constitues a Marked PPP, where the marks are the channel power gains

$$\mathrm{PDF}_{r_0}\left(\xi\right) = 2\pi\lambda\xi \exp\left(-\pi\lambda\xi^2\right)$$

The PDF of the closest-distance follows from the null probability of spatial PPPs

$$\mathrm{MGF}_{I_{agg}\left(r_0\right)}\left(s\right) = \ldots$$

The MGF of the aggregate other-cell interference follows from the Probability Generating Functional (PGFL) of Marked PPPs

How It Works: The Magic of Stochastic Geometry (5/5)

… understanding the basic math …

$$\mathrm{MGF}_{I_{agg}(r_0)}(s) = \mathrm{E}_{\Phi,\{|h_i|^2\}}\left\{\exp\left(-s\sum_{i\in\Phi\backslash BS_0} P|h_i|^2 r_i^{-\alpha}\right)\right\}$$

$$= \mathrm{E}_{\Phi}\left\{\prod_{i\in\Phi\backslash BS_0} \mathrm{E}_{\{|h_i|^2\}}\left\{\exp\left(-sP|h_i|^2 r_i^{-\alpha}\right)\right\}\right\}$$

$$(\mathrm{PGFL} \Rightarrow) = \exp\left(-2\pi\lambda \underbrace{\int_{r_0}^{+\infty}\left(1-\mathrm{E}_{|h_i|^2}\left\{\exp\left(-sP|h_i|^2 \xi_i^{-\alpha}\right)\right\}\right)\xi_i d\xi_i}_{\text{available in closed-form in papers}}\right)$$

So Powerful and Just Two Lemmas Need to be Used…

Sums over PPP

Lemma (Campbells theorem)

Let Φ be a PPP of density λ and $f(x) : \mathbb{R}^2 \to \mathbb{R}^+$.

$$\mathbb{E}[\sum_{x\in\Phi} f(x)] = \lambda \int_{\mathbb{R}^2} f(x)\mathrm{d}x$$

Products over PPP

Lemma (Probability generating functional (PGFL))

Let Φ be a PPP of density λ and $f(x) : \mathbb{R}^2 \to [0,1]$ be a real valued function. Then

$$\mathbb{E}\left[\prod_{x\in\Phi} f(x)\right] = \exp\left(-\lambda \int_{\mathbb{R}^2} (1 - f(x))\mathrm{d}x\right).$$

Stochastic Geometry: Advantages and Limitations

- **Advantages: "What the Lovers Say"**
  - **Elegant mathematical formulation for network-wide performance metrics**
  - **Often closed-form and insightful**
  - **Provides utility functions for system design and optimization**
  - **…**

- **Limitations: "What the Others Say" – MISCONCEPTION**
  - **The PPP assumption may not be realistic for some tiers of BSs**
  - **Practical transmission technologies are more complicated than SISO**
  - **Practical path-loss models are bounded and different for LOS/NLOS**
  - **Practical channel models are more complicated than Rayleigh fading**
  - **Closed-form formulation only for specific parameters**
  - ***In general, one or two integrals need to be accepted***
  - **…**

Three New and General Mathematical Tools

1. **Average Rate: The MGF-Based Approach**
   - **M. Di Renzo, A. Guidotti, and G. E. Corazza, "Average Rate of Downlink Heterogeneous Cellular Networks over Generalized Fading Channels – A Stochastic Geometry Approach", IEEE Trans. Commun., vol. 61, no. 7, pp. 3050–3071, July 2013.**

2. **Average Error Probability: The EiD-Based Approach**
   - **M. Di Renzo and W. Lu, "The Equivalent–in–Distribution (EiD)–based Approach: On the Analysis of Cellular Networks Using Stochastic Geometry", IEEE Commun. Lett., vol. 18, no. 5, pp. 761-764, May 2014.**
   - **M. Di Renzo and W. Lu, "Stochastic Geometry Modeling and Performance Evaluation of MIMO Cellular Networks by Using the Equivalent-in-Distribution (EiD)-Based Approach", IEEE Trans. Commun., vol. 63, no. 3, pp. 977-996, March 2015.**

3. **Coverage Probability: The Gil-Pelaez-Based Approach**
   - **M. Di Renzo and P. Guan, "Stochastic Geometry Modeling of Coverage and Rate of Cellular Networks Using the Gil-Pelaez Inversion Theorem", IEEE Commun. Lett., vol. 18, no. 9, pp. 1575–1578, September 2014.**

Many Tools/Results are Now Available…

- M. Di Renzo, C. Merola, A. Guidotti, F. Santucci, and G. E. Corazza, "Error Performance of Multi–Antenna Receivers in a Poisson Field of Interferers – A Stochastic Geometry Approach", IEEE Trans. Commun., vol. 61, no. 5, pp. 2025–2047, May 2013.
- M. Di Renzo, A. Guidotti, and G. E. Corazza, "Average Rate of Downlink Heterogeneous Cellular Networks over Generalized Fading Channels – A Stochastic Geometry Approach", IEEE Trans. Commun., vol. 61, no. 7, pp. 3050–3071, July 2013.
- M. Di Renzo and W. Lu, "The Equivalent–in–Distribution (EiD)–based Approach: On the Analysis of Cellular Networks Using Stochastic Geometry", IEEE Commun. Lett., vol. 18, no. 5, pp. 761-764, May 2014.
- M. Di Renzo and P. Guan, "A Mathematical Framework to the Computation of the Error Probability of Downlink MIMO Cellular Networks by Using Stochastic Geometry", IEEE Trans. Commun., vol. 62, no. 8, pp. 2860–2879, July 2014.
- M. Di Renzo and P. Guan, "Stochastic Geometry Modeling of Coverage and Rate of Cellular Networks Using the Gil-Pelaez Inversion Theorem", IEEE Commun. Lett., vol. 18, no. 9, pp. 1575–1578, September 2014.
- M. Di Renzo and W. Lu, "End-to-End Error Probability and Diversity Analysis of AF-Based Dual-Hop Cooperative Relaying in a Poisson Field of Interferers at the Destination", IEEE Trans. Wireless Commun., vol. 14, no. 1, pp. 15–32, January 2015.
- M. Di Renzo and W. Lu, "Stochastic Geometry Modeling and Performance Evaluation of MIMO Cellular Networks by Using the Equivalent-in-Distribution (EiD)-Based Approach", IEEE Trans. Commun., vol. 63, no. 3, pp. 977-996, March 2015.
- M. Di Renzo and W. Lu, "On the Diversity Order of Selection Combining Dual-Branch Dual-Hop AF Relaying in a Poisson Field of Interferers at the Destination", IEEE Trans. Veh. Technol., vol. 64, no. 4, pp. 1620-1628, June 2015.

… and, Recently, Have Been Proposed

- M. Di Renzo, "Stochastic Geometry Modeling and Analysis of Multi-Tier Millimeter Wave Cellular Networks", IEEE Trans. Wireless Commun., vol. 14, no. 9, pp. 5038-5057, Sep. 2015.
- W. Lu and M. Di Renzo, "Stochastic Geometry Modeling and System-Level Analysis/Optimization of Relay-Aided Downlink Cellular Networks", IEEE Trans. Commun., vol 63, no. 11, pp. 4063-4085, Nov. 2015.
- M. Di Renzo and P. Guan, "Stochastic Geometry Modeling, System-Level Analysis and Optimization of Uplink Heterogeneous Cellular Networks with Multi-Antenna Base Stations", IEEE Trans. Commun., IEEE Early Access.
- M. Di Renzo and W. Lu, "System-Level Analysis/Optimization of Cellular Networks with Simultaneous Wireless Information and Power Transfer: Stochastic Geometry Modeling", IEEE Trans. Vehicular Technol., IEEE Early Access.
- F. J. Martin-Vega, G. Gomez, M. C. Aguayo Torres, and M. Di Renzo, "Analytical Modeling of Interference Aware Power Control for the Uplink of Heterogeneous Cellular Networks", IEEE Trans. Wireless Commun., IEEE Early Access.
- Y. Deng, L. Wang, M. Elkashlan, M. Di Renzo, and J. Yuan, "Modeling and Analysis of Wireless Power Transfer in Heterogeneous Cellular Networks", IEEE Trans. Commun., IEEE Early Access.

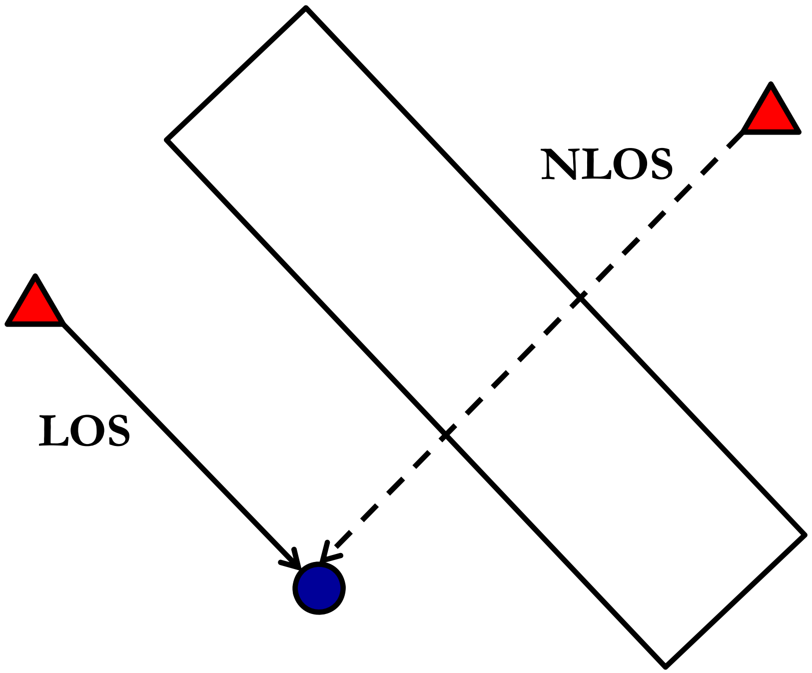
… and, Recently, Have Been Proposed

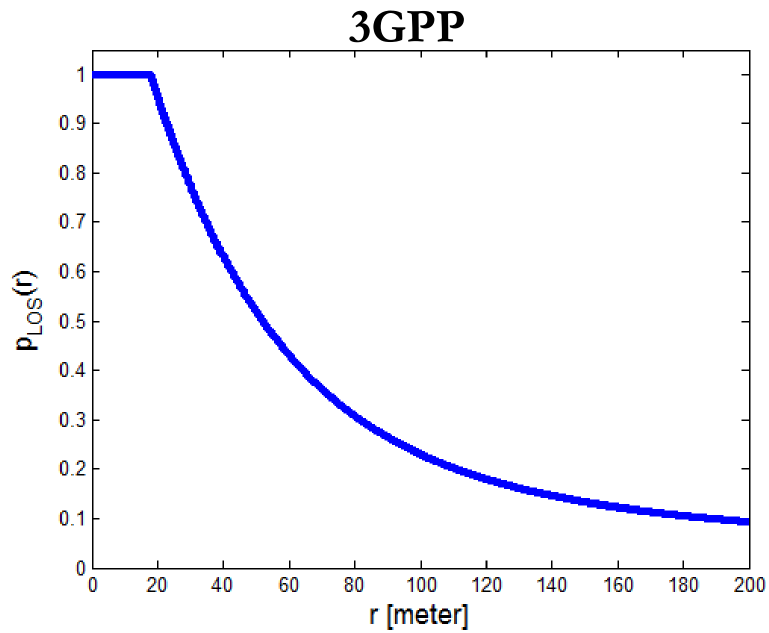
A Complete Mathematical Framework for System-Level Analysis

- **M. Di Renzo, W. Lu, and P. Guan, "The Intensity Matching Approach: A Tractable Stochastic Geometry Approximation to System-Level Analysis of Cellular Networks", IEEE Trans. Wireless Commun., IEEE Early Access.**
  - **Realistic path-loss model with LOS/NLOS conditions**
  - **Arbitrary shadowing and fading**
  - **General antenna-array radiation pattern**
  - **Multi-tier topology with practical cell association**
  - **Realistic traffic load models as a function of the densities of BSs and MTs**
  - **…**

IM Approach: Why So Many Details are Needed?

... Impact of LOS/NLOS ...





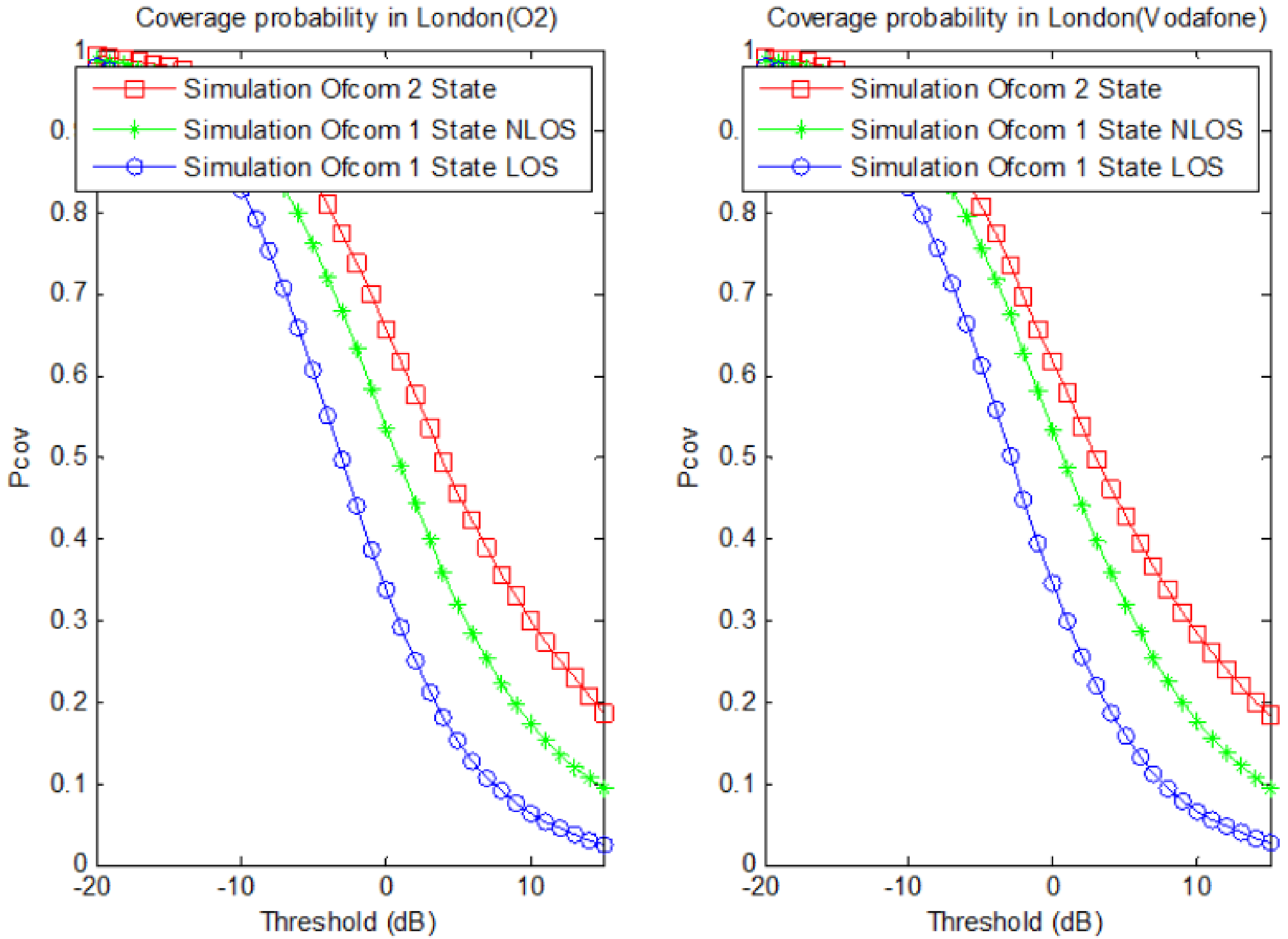
$$p_{\mathrm{LOS}}(r) = \min\left\{\frac{18}{r}, 1\right\}\left(1 - e^{-\frac{r}{36}}\right) + e^{-\frac{r}{36}}$$

Mobile terminal

Base station

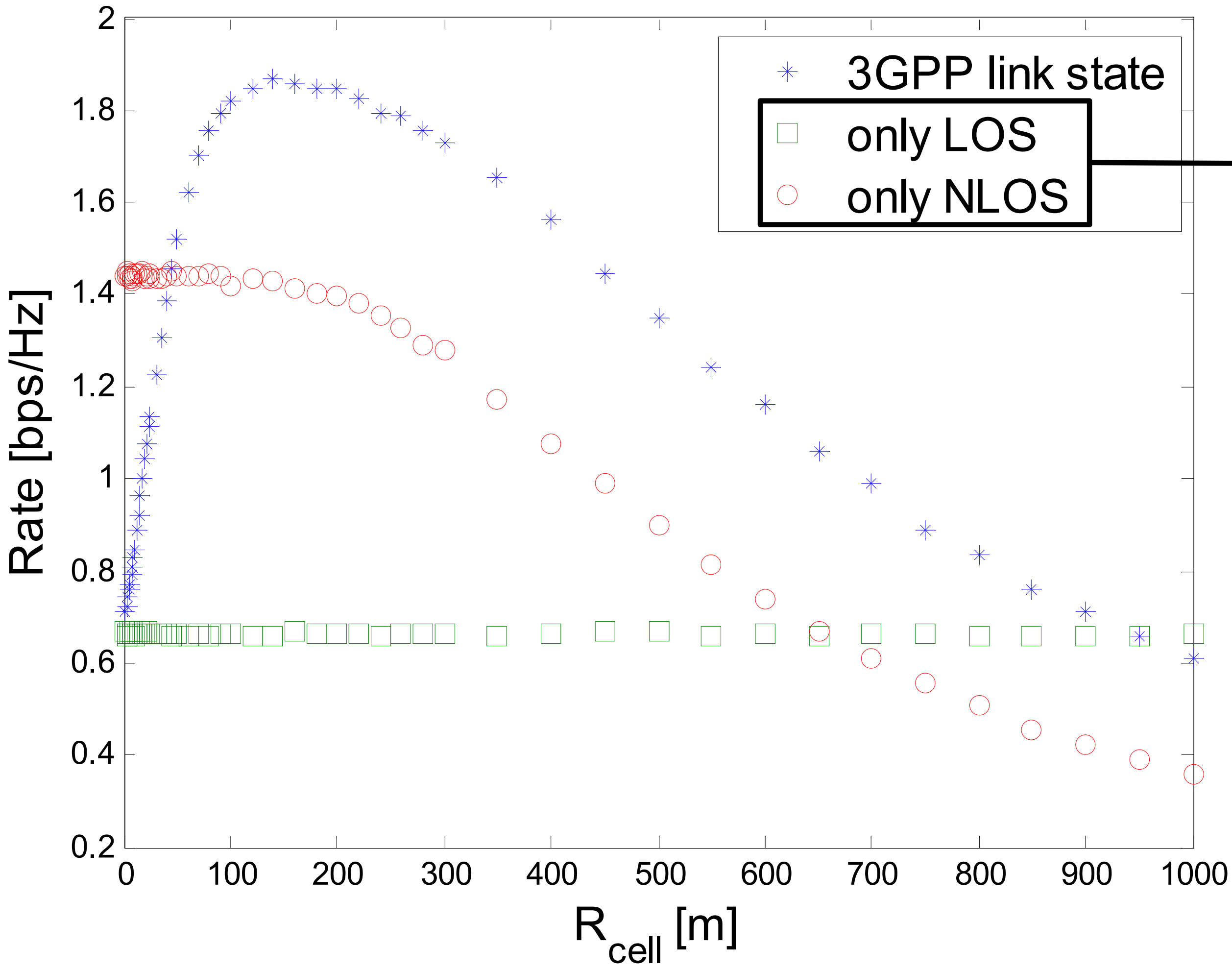
IM Approach: Why So Many Details are Needed?

… Impact of LOS/NLOS …



IM Approach: Why So Many Details are Needed?

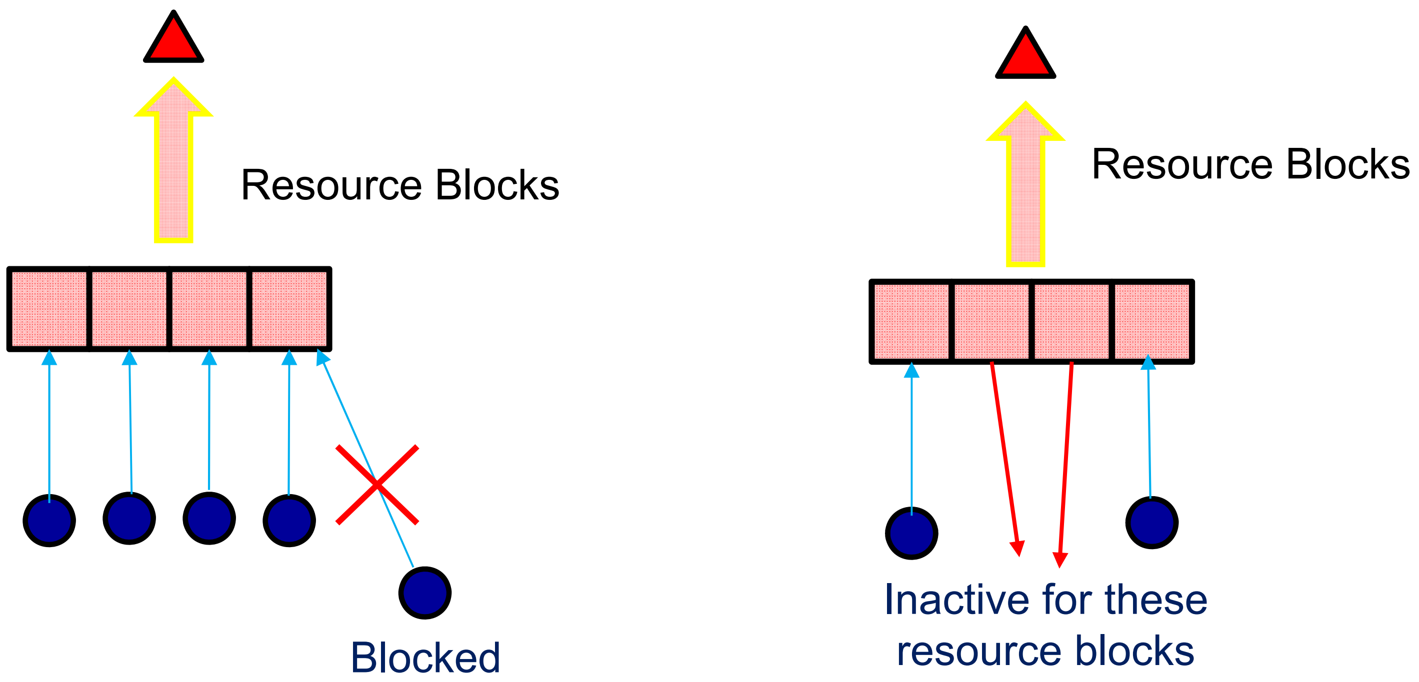
... Impact of LOS/NLOS (fully-loaded) …



Current assumption (for tractability) in stochastic geometry modeling (99.99% of papers)

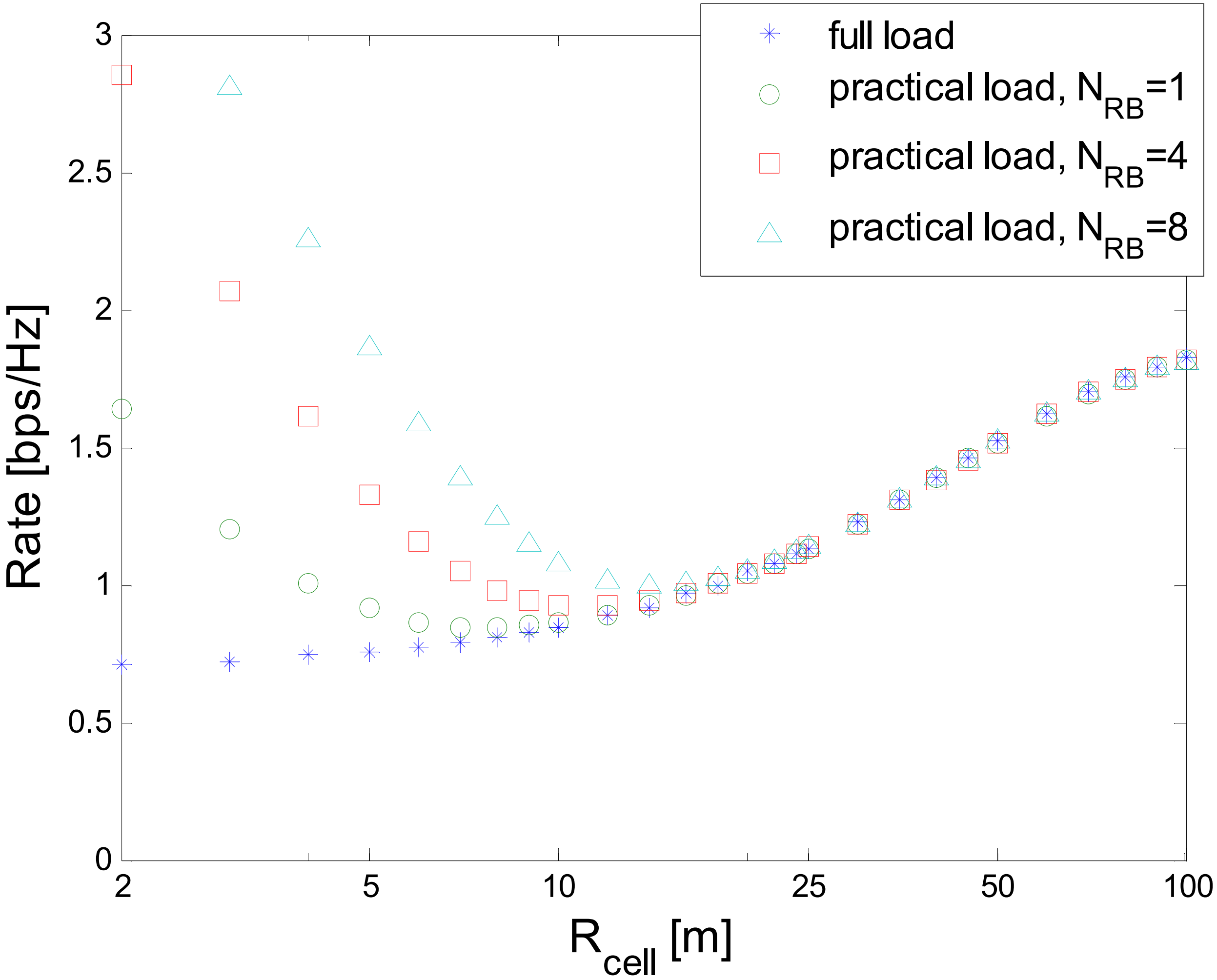
IM Approach: Why So Many Details are Needed?

… Impact of Load of Base Stations …



IM Approach: Why So Many Details are Needed?

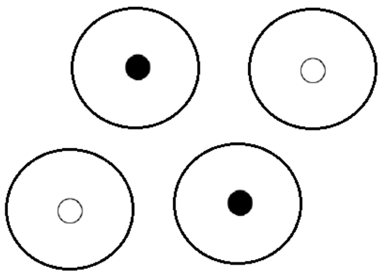
… Impact of Load of Base Stations …



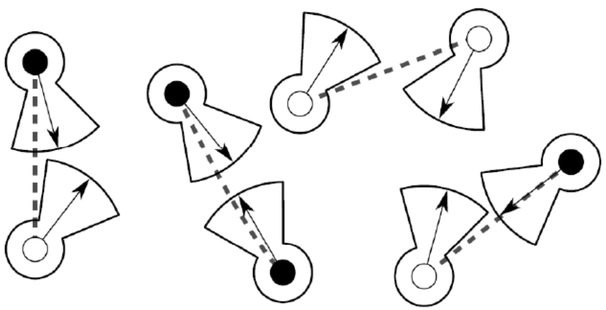
IM Approach: Why So Many Details are Needed?

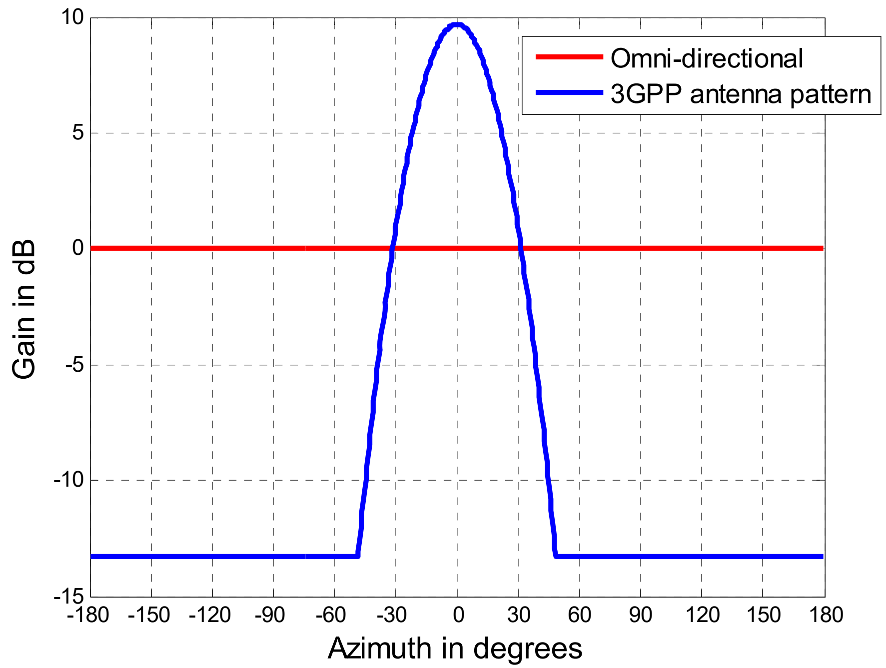
… Impact of Antenna Directionality …

Omni-directional antennas



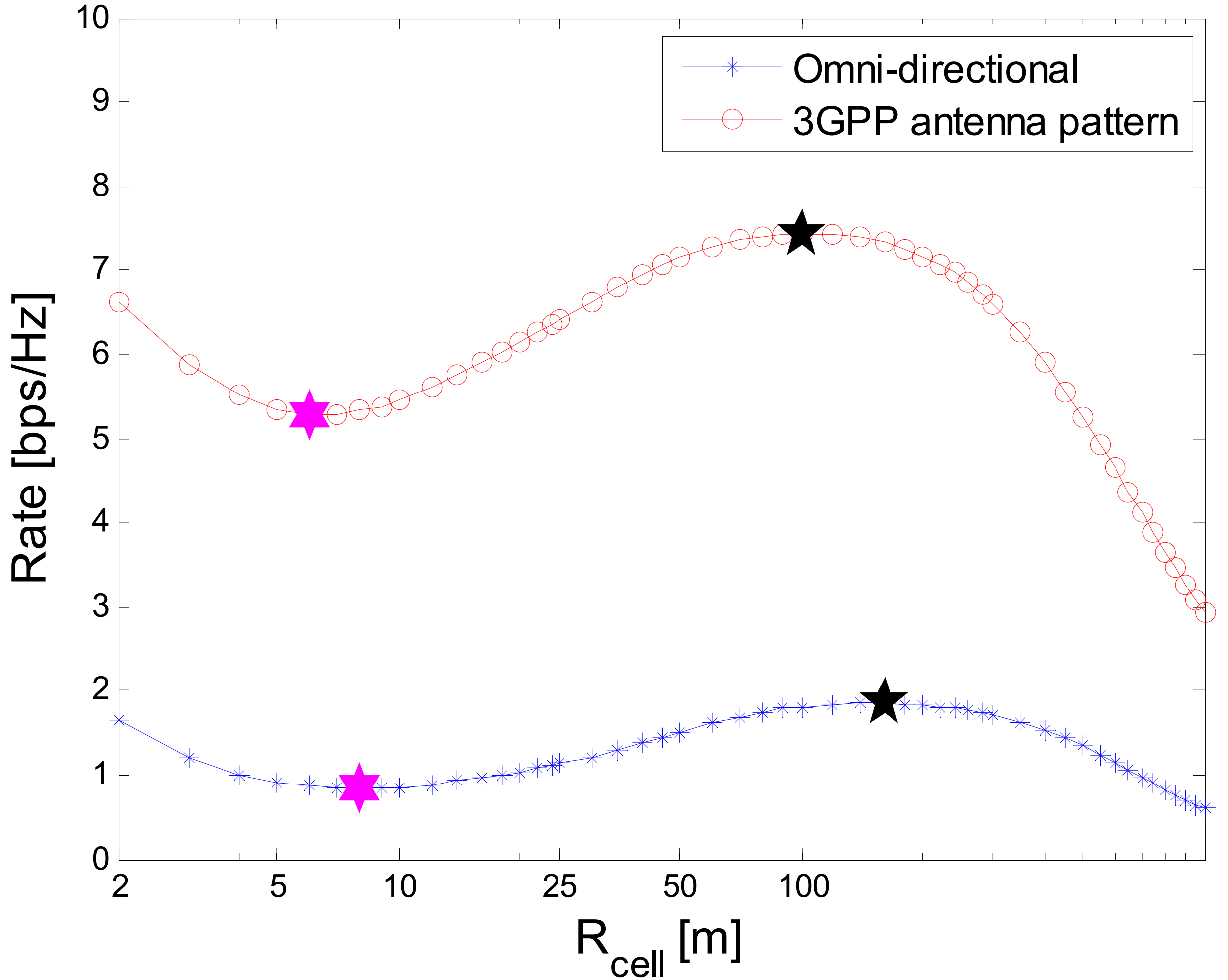
Directional antennas





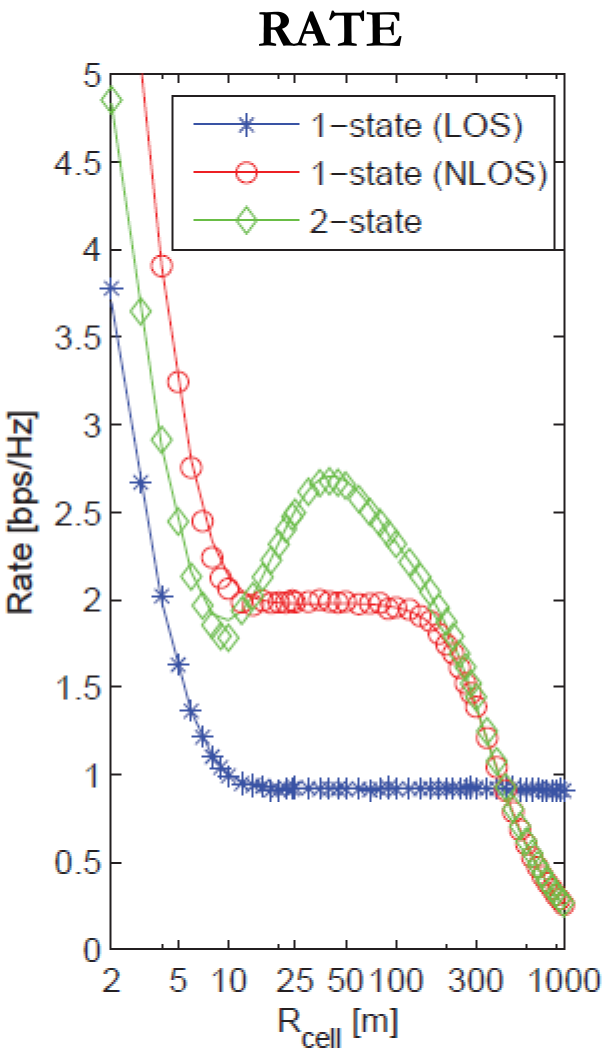
IM Approach: Why So Many Details are Needed?

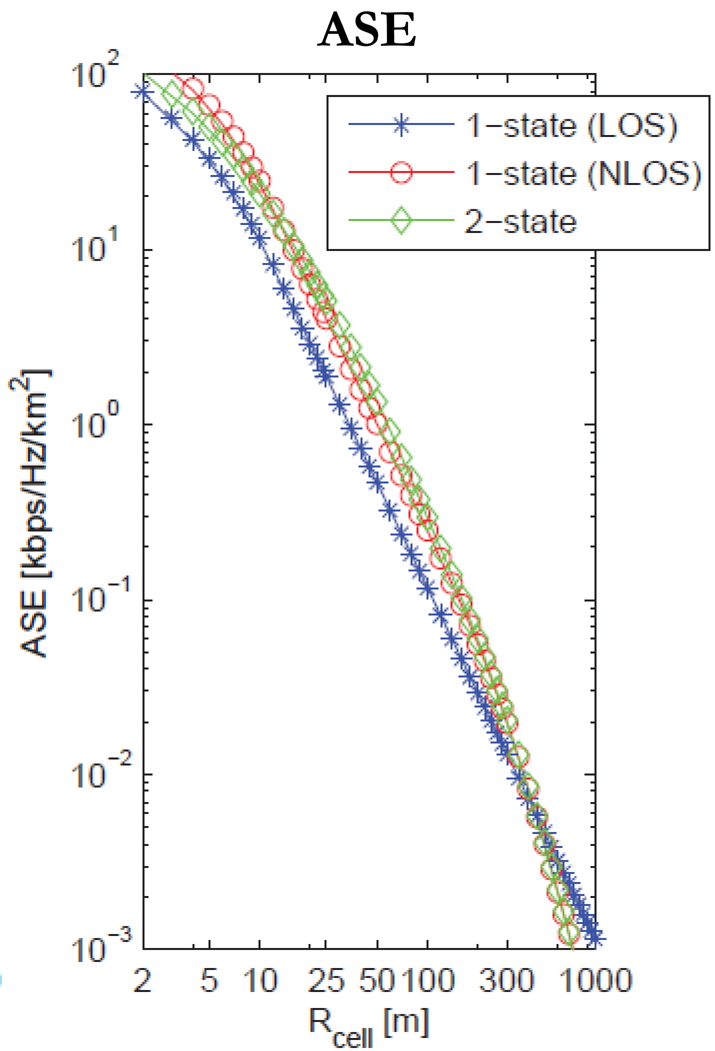
... Impact of Antenna Directionality …



IM Approach: Why So Many Details are Needed?

... Sub-Linear Trend of the Area Spectral Efficiency ...





Intrigued Enough? On Experimental Validation…

Stochastic Geometry Modeling of Cellular Networks: Analysis, Simulation and Experimental Validation

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ABSTRACT

Due to the increasing heterogeneity and deployment density of emerging cellular networks, new flexible and scalable approaches for their modeling, simulation, analysis and optimization are needed. Recently, a new approach has been proposed: it is based on the theory of point processes and it leverages tools from stochastic geometry for tractable system-level modeling, performance evaluation and optimization. In this paper, we investigate the accuracy of this emerging abstraction for modeling cellular networks, by explicitly taking realistic base station locations, building footprints, spatial blockages and antenna radiation patterns into account. More specifically, the base station locations and the building footprints are taken from two publicly available databases from the United Kingdom. Our study confirms that the abstraction model based on stochastic geometry is capable of accurately modeling the communication performance of cellular networks in dense urban environments.

pected to provide [1]. Modeling, simulating, analyzing and optimizing such networks is, however, a non-trivial problem. This is due to the large number of access points that are expected to be deployed and their dissimilar characteristics, which encompass deployment density, transmit power, access technology, etc. Motivated by these considerations, several researchers are investigating different options for modeling, simulating, mathematically analyzing and optimizing these networks. The general consensus is, in fact, that the methods used in the past for modeling cellular networks, e.g., the hexagonal grid-based model [2], are not sufficiently scalable and flexible for taking the ultra-dense and irregular deployments of emerging cellular topologies into account.

Recently, a new approach for overcoming these limitations has been proposed. It is based on the theory of point processes (PP) and leverages tools from stochastic geometry for system-level modeling, performance evaluation and optimization of cellular networks [3]. In this paper, it is referred

W. Lu and M. Di Renzo, "Stochastic Geometry Modeling of Cellular Networks: Analysis, Simulation and Experimental Validation", ACM Int. Conf. Modeling, Analysis and Simulation of Wireless and Mobile Systems, Nov. 2015. [Online]. Available: http://arxiv.org/pdf/1506.03857.pdf.

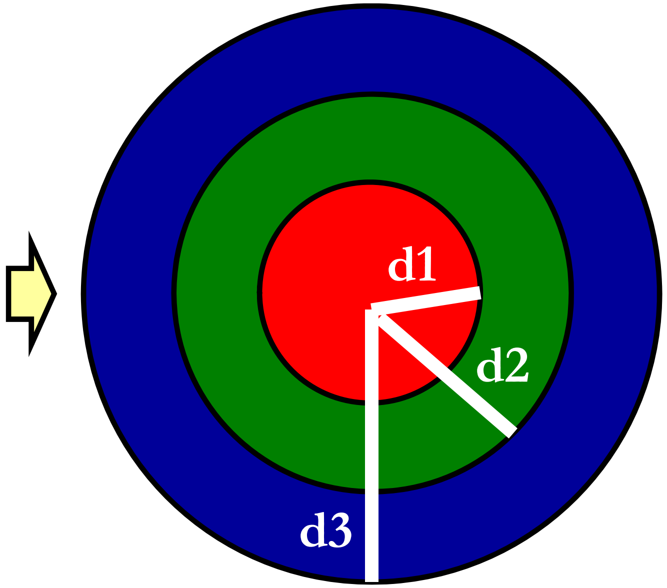
W. Lu and M. Di Renzo, "Stochastic Geometry Modeling of mmWave Cellular Networks: Analysis and Experimental Validation", IEEE Int. Workshop on Measurement and Networking (M&N) – Special Session on Advances in 5G Wireless Networks, Oct. 12-13, 2015.

Rationale of IM Approach: Multi-Ball Approximation

… the approach (e.g., 3-ball case) …

- **Practical link-state models are approximated using a multi-ball model**
- **The related parameters are computed using the "intensity matching" criterion**

	$p_{\mathrm{LOS}}(r)$	$p_{\mathrm{NLOS}}(r)$
3GPP model	$\min\left\{\frac{18}{r},1\right\}\left(1-e^{-\frac{r}{36}}\right)+e^{-\frac{r}{36}}$	$1-p_{\mathrm{LOS}}(r)$
Random Shape	$\gamma_{\mathrm{RS}}\exp\left(-\beta_{\mathrm{RS}}r\right)$	$1-p_{\mathrm{LOS}}(r)$
Linear model	$1-p_{\mathrm{NLOS}}(r)$	$\min\left\{a_{\mathrm{LM}}r+b_{\mathrm{LM}},c_{\mathrm{LM}}\right\}$
Statistical mmWave	$\left(1-p_{\mathrm{OUT}}\left(r\right)\right)e^{-a_{\mathrm{LOS}}r}$	$1-p_{\mathrm{LOS}}(r)-p_{\mathrm{OUT}}(r)$



$$p_S\left(r\right)=\sum_{n=1}^{N=3}q_S^{\left[d_{n-1},d_n\right]}\mathbf{1}_{\left[d_{n-1},d_n\right)}\left(r\right)\quad\text{with}\quad\sum_{S\in\{\mathrm{LOS},\mathrm{NLOS},\ldots\}}q_S^{\left[d_{n-1},d_n\right]}=1\quad\forall n=1,2,\ldots,N$$

$$\text{minimize}\left\{\left\|\ln\left(\sum_{S\in\{\mathrm{LOS},\mathrm{NLOS},\ldots\}}\Lambda_{r_0,S}^{(\mathrm{actual})}\left(\left[0,x_{\max}\right)\right)\right)-\ln\left(\sum_{S\in\{\mathrm{LOS},\mathrm{NLOS},\ldots\}}\Lambda_{r_0,S}^{(\mathrm{approx})}\left(\left[0,x_{\max}\right)\right)\right)\right\|_F^2\right\}$$

Rationale of IM Approach: Multi-Ball Approximation

Why Matching the Intensity Measures ?

- **Consider the general association criterion as follows:**

$$\mathrm{BS}_0 \text{ is chosen as the minimum of the set } \Psi = \left\{ \frac{l(r_n)}{\Upsilon_n}, n \in \Phi \right\}$$

Φ is a (non-homogeneous) PPP of BSs with density λ(r) = λ*p(r)

l(r) denotes the path-loss function

Υ is a random variable that accounts for all random variables that are taken into account for cell association except for the distance (e.g., shadowing)

- **Based on the displacement theorem of PPPs, the set Ψ is a PPP in R^+ whose intensity measure is the following:**

$$\Lambda_\Psi([0,x)) = 2\pi\lambda \int_0^{+\infty} \Pr\left\{ \frac{l(r)}{\Upsilon} \in [0,x) \right\} p(r) r dr$$

$$= 2\pi\lambda \mathrm{E}_\Upsilon \left\{ \int_0^{+\infty} \Pr\left\{ l(r) \in [0, x\xi) \middle| \Upsilon = \xi \right\} p(r) r dr \right\}$$

Rationale of IM Approach: Multi-Ball Approximation

Why Matching the Intensity Measures ?

- **Since the intensity measure is now known and Ψ is still a PPP, the coverage probability can be formulated, after some algebra, as follows:**

$$\tilde{l}_{\mathrm{LOS}} = \min_{\Psi}\left\{ l_{\mathrm{LOS}}(r) / \Upsilon_{\mathrm{LOS}} \right\} \qquad \tilde{l}_{\mathrm{NLOS}} = \min_{\Psi}\left\{ l_{\mathrm{NLOS}}(r) / \Upsilon_{\mathrm{NLOS}} \right\}$$

$$\boxed{\begin{aligned}
\mathrm{P}_{\mathrm{cov}} &= \mathrm{E}_{\tilde{l}_{\mathrm{LOS}}}\left\{ \Pr\left\{ \frac{P\left|\tilde{h}_{o,\mathrm{LOS}}\right|^2 / \tilde{l}_{\mathrm{LOS}}}{\sigma^2 + I_{agg}\left(\tilde{l}_{\mathrm{LOS}}\right)} > T \,\middle|\, \tilde{l}_{\mathrm{LOS}} \right\} \Pr\left\{ \tilde{l}_{\mathrm{NLOS}} > \tilde{l}_{\mathrm{LOS}} \,\middle|\, \tilde{l}_{\mathrm{LOS}} \right\} \right\} \\
&\quad + \mathrm{E}_{\tilde{l}_{\mathrm{NLOS}}}\left\{ \Pr\left\{ \frac{P\left|\tilde{h}_{o,\mathrm{NLOS}}\right|^2 / \tilde{l}_{\mathrm{NLOS}}}{\sigma^2 + I_{agg}\left(\tilde{l}_{\mathrm{NLOS}}\right)} > T \,\middle|\, \tilde{l}_{\mathrm{LOS}} \right\} \Pr\left\{ \tilde{l}_{\mathrm{LOS}} > \tilde{l}_{\mathrm{NLOS}} \,\middle|\, \tilde{l}_{\mathrm{NLOS}} \right\} \right\} \\
&= \int_0^{+\infty} \Pr\left\{ \frac{P\left|\tilde{h}_{o,\mathrm{LOS}}\right|^2 / x}{\sigma^2 + I_{agg}(x)} > T \,\middle|\, x \right\} \mathrm{CCDF}_{\tilde{l}_{\mathrm{NLOS}}}(x)\, \mathrm{PDF}_{\tilde{l}_{\mathrm{LOS}}}(x)\, dx \\
&\quad + \int_0^{+\infty} \Pr\left\{ \frac{P\left|\tilde{h}_{o,\mathrm{NLOS}}\right|^2 / y}{\sigma^2 + I_{agg}(y)} > T \,\middle|\, y \right\} \mathrm{CCDF}_{\tilde{l}_{\mathrm{LOS}}}(y)\, \mathrm{PDF}_{\tilde{l}_{\mathrm{NLOS}}}(y)\, dy
\end{aligned}}$$

Rationale of IM Approach: Multi-Ball Approximation

Why Matching the Intensity Measures ?

$$\mathrm{CCDF}_{\tilde{l}_S}(\xi) \overset{\text{void probability th.}}{=} \exp\left(-\Lambda_{\Psi_S}([0,\xi))\right) \Rightarrow \mathrm{PDF}_{\tilde{l}_S}(\xi) = -d\mathrm{CCDF}_{\tilde{l}_S}(\xi)/d\xi$$

$$\mathrm{MGF}_{I_{agg},Q}\left(w;\tilde{l}_S\right)\left(\Leftarrow \mathrm{MGF}_{I_{agg}}\left(w;\tilde{l}_S\right) = \mathrm{MGF}_{I_{agg},\mathrm{LOS}}\left(w;\tilde{l}_S\right)\mathrm{MGF}_{I_{agg},\mathrm{NLOS}}\left(w;\tilde{l}_S\right)\right)$$

$$= \mathrm{E}_{\Phi_Q,\left\{\left|\tilde{h}_{k,Q}\right|^2\right\}}\left\{\exp\left(-w\sum\nolimits_{k\in\Phi_Q}\left(P\left|\tilde{h}_{k,Q}\right|^2/\tilde{l}_{k,Q}\right)\mathbf{1}\left(\tilde{l}_{k,Q} > \tilde{l}_S\right)\right)\right\}$$

$$= \mathrm{E}_{\Phi_Q}\left\{\prod\nolimits_{k\in\Phi_Q}\mathrm{E}_{\left\{\left|\tilde{h}_{k,Q}\right|^2\right\}}\left\{\exp\left(-w\left(P\left|\tilde{h}_{k,Q}\right|^2/\tilde{l}_{k,Q}\right)\mathbf{1}\left(\tilde{l}_{k,Q} > \tilde{l}_S\right)\right)\right\}\right\}$$

$$\overset{\text{PGFL}}{=} \exp\left(-\int_{\tilde{l}_S}^{+\infty}\left(1-\mathrm{E}_{\left|\tilde{h}_{k,Q}\right|^2}\left\{\exp\left(-w\left(P\left|\tilde{h}_{k,Q}\right|^2/l\right)\right)\right\}\right)\underbrace{\Lambda_{\Psi_Q}^{(1)}([0,l))}_{=d/dl\left(\Lambda_{\Psi_Q}([0,l))\right)}dl\right)$$

Intrigued Enough? On Mathematical Modeling…

The Intensity Matching Approach: A Tractable Stochastic Geometry Approximation to System-Level Analysis of Cellular Networks

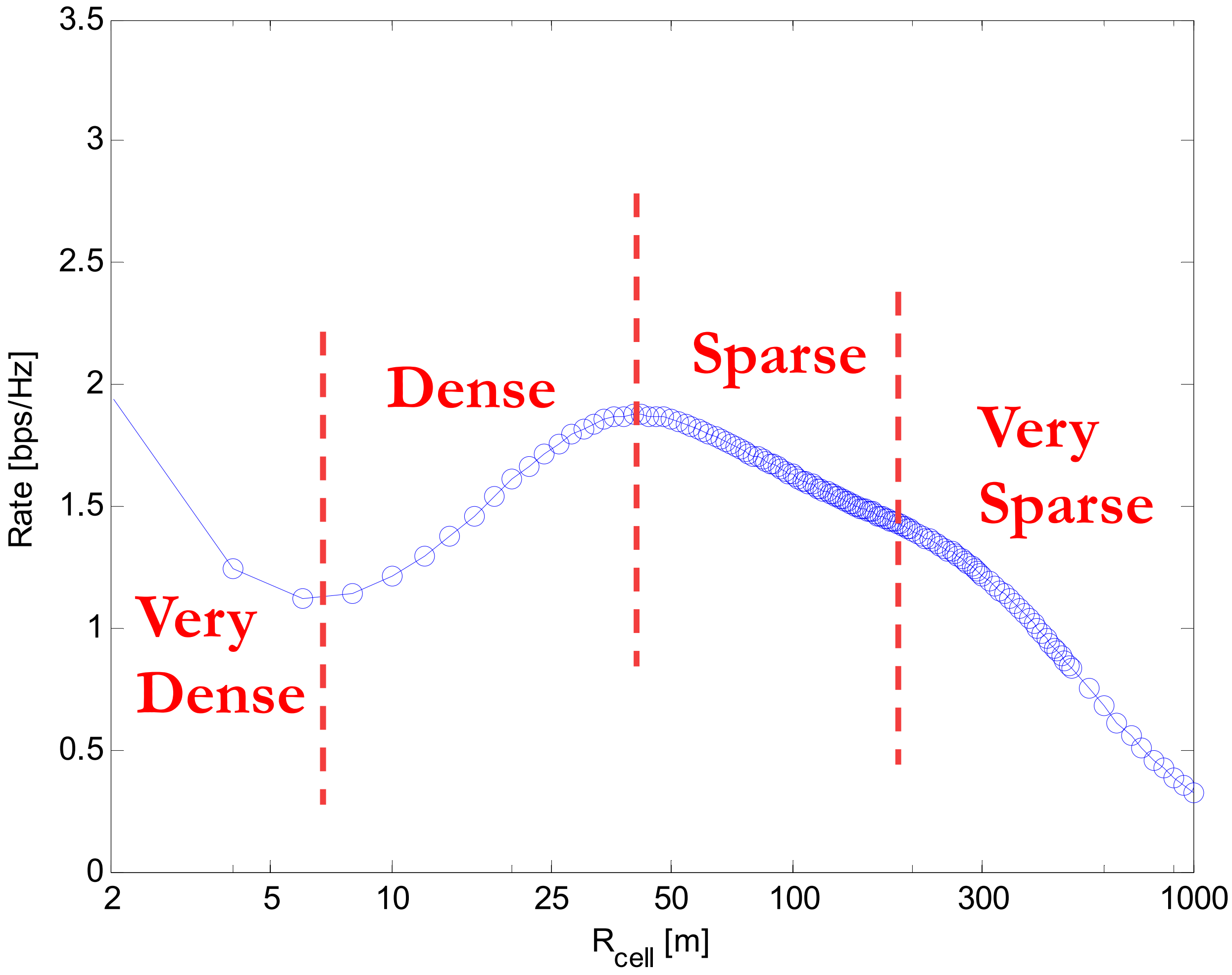
Marco Di Renzo, *Senior Member, IEEE*, Wei Lu, *Student Member, IEEE*, and Peng Guan, *Student Member, IEEE*

Abstract

The intensity matching approach for tractable performance evaluation and optimization of cellular networks is introduced. It assumes that the base stations are modeled as points of a Poisson point process and leverages stochastic geometry for system-level analysis. Its rationale relies on observing that system-level performance is determined by the intensity measure of transformations of the underlaying spatial Poisson point process. By approximating the original system model with a simplified one, whose performance is determined by a mathematically convenient intensity measure, tractable yet accurate integral expressions for computing area spectral efficiency and potential throughput are provided. The considered system model accounts for many practical aspects that, for tractability, are typically neglected, *e.g.*, line-of-sight and non-line-of-sight propagation, antenna radiation patterns, traffic load, practical cell associations, general fading channels. The proposed approach, more importantly, is conveniently formulated for unveiling the impact of several system parameters, *e.g.*, the density of base stations and blockages. The effectiveness of this novel and general methodology is validated with the aid of empirical data for the locations of base stations and for the footprints of buildings in a dense urban environment.

M. Di Renzo et al., "The Intensity Matching Approach: A Tractable Stochastic Geometry Approximation to System-Level Analysis of Cellular Networks", IEEE Trans. Wireless Commun., IEEE Early Access.

The Intensity Matching Approach: Main Takes



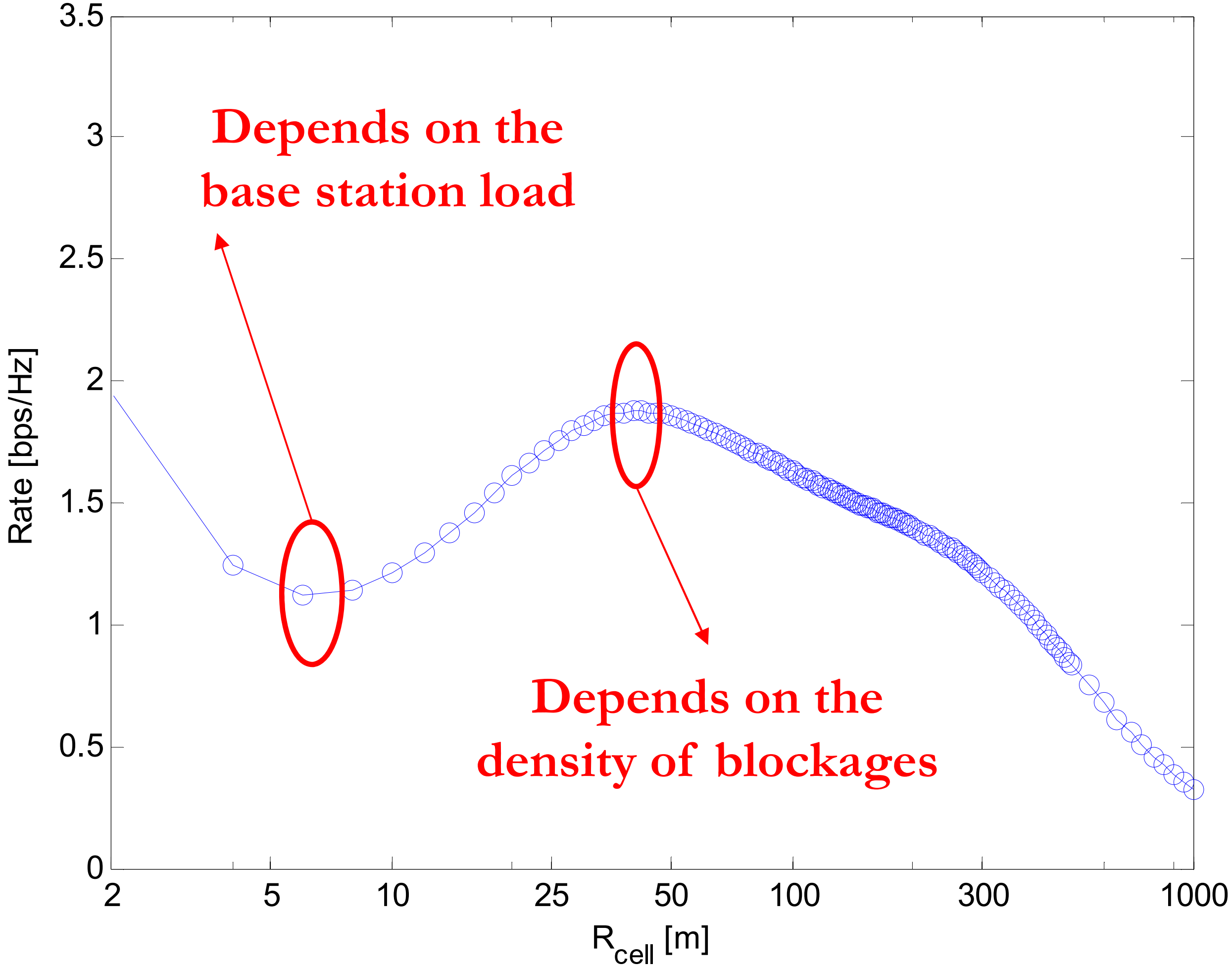
M. Di Renzo et al., "The Intensity Matching Approach: A Tractable Stochastic Geometry Approximation to System-Level Analysis of Cellular Networks", IEEE Trans. Wireless Commun., IEEE Early Access.

The Intensity Matching Approach: Main Takes

	Very Dense (VD) Networks	Dense (D) Networks	Sparse (S) Networks	Very Sparse (VS) Networks
$\lambda_{\mathrm{BS}} \nearrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate $\searrow$ – ASE ?	Rate $\nearrow$ – ASE $\nearrow$	Rate $\nearrow$ – ASE $\nearrow$
$\lambda_{\mathrm{MT}} \nearrow$	Rate $\searrow$ – ASE $\nearrow$	Rate $\leftrightarrow$ – ASE $\leftrightarrow$	Rate $\leftrightarrow$ – ASE $\leftrightarrow$	Rate $\leftrightarrow$ – ASE $\leftrightarrow$
$N_{\mathrm{RB}} \nearrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate $\leftrightarrow$ – ASE $\nearrow$	Rate $\searrow$ – ASE $\nearrow$	Rate $\searrow$ – ASE $\nearrow$
$P_{\mathrm{BS}} \nearrow$	Rate $\leftrightarrow$ – ASE $\leftrightarrow$	Rate $\leftrightarrow$ – ASE $\leftrightarrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate $\nearrow$ – ASE $\nearrow$
$G^{(0)} \nearrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate $\nearrow$ – ASE $\nearrow$
$D_1 \nearrow$	Rate $\searrow$ – ASE $\searrow$	Rate $\searrow$ – ASE $\searrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate $\leftrightarrow$ – ASE $\leftrightarrow$
$\sigma_s \nearrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate $\nearrow$ – ASE $\nearrow$	Rate ? – ASE ?	Rate $\nearrow$ – ASE $\nearrow$

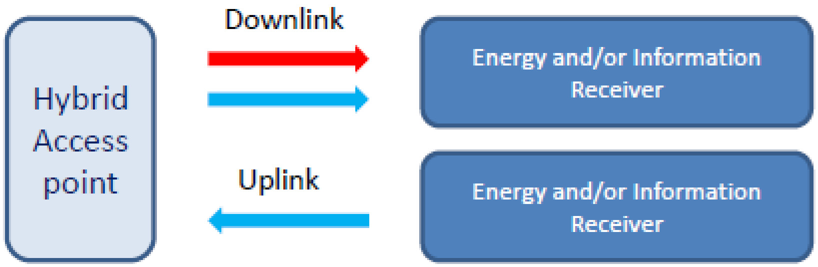
M. Di Renzo et al., "The Intensity Matching Approach: A Tractable Stochastic Geometry Approximation to System-Level Analysis of Cellular Networks", IEEE Trans. Wireless Commun., IEEE Early Access.

The Intensity Matching Approach: Main Takes



M. Di Renzo et al., "The Intensity Matching Approach: A Tractable Stochastic Geometry Approximation to System-Level Analysis of Cellular Networks", IEEE Trans. Wireless Commun., IEEE Early Access.

SWIPT – System-Level Modeling and Optimization



Major Difference:

Information (rate) and harvesting (energy) requirements need to be jointly satisfied

Setup: LOS/NLOS, beamforming, etc.

Harvesting: Interference is GOOD

$$\mathcal{Q} = \eta\zeta\left(\mathrm{U}^{(0)} + \mathrm{I}_{\mathrm{agg}}\right)$$

Information: Interference is BAD

$$\mathcal{R} = \mu \mathrm{B_W} \log_2\left(1 + \frac{\mathrm{U}^{(0)}}{\sigma_{\mathrm{N}}^2 + \sigma_{\mathrm{C}}^2 + \mathrm{I}_{\mathrm{agg}}}\right)$$

Joint Statistical Characterization of Harvested Energy and Achievable Rate in the Presence of Other-Cell Interference

$$\mathcal{F}_{\mathrm{c}}\left(\mathcal{Q}_0, \mathcal{R}_0\right) = \Pr\left\{\mathcal{Q} \geq \mathcal{Q}_0, \mathcal{R} \geq \mathcal{R}_0\right\}$$

$$\mathcal{F}_{\mathrm{c}}\left(\mathcal{Q}_0, \mathcal{R}_0\right) \approx \int_0^{\mathcal{M}} \left[\int_0^{+\infty} (\pi\omega)^{-1} \operatorname{Im}\left\{\mathcal{Y}(\omega, x)\, \Phi_{\mathrm{I_{agg}}}^{(\mathrm{RP})}(\omega | x)\right\} f_{P^{(0)}}(x)\, d\omega\right] dx$$

M. Di Renzo and W. Lu, "System-Level Analysis of Cellular Networks with Simultaneous Wireless Information and Power Transfer: Stochastic Geometry Modeling", IEEE Trans. Vehicular Technol., IEEE Early Access.

Appendix II – Proof of Proposition 2

For ease of description, we set $\mathrm{U}^{(0)} = \mathrm{U}^{(0)}\left(P^{(0)}\right) = \mathrm{P}G^{(0)}/P^{(0)}$ and $\mathrm{I}_{\mathrm{agg}} = \mathrm{I}_{\mathrm{agg}}\left(P^{(0)}\right)$ as defined in (21). By using mathematical steps similar to [51, Eq. (21)], $\mathcal{F}_{\mathrm{c}}(\cdot,\cdot)$ can be formulated as follows:

$$\mathcal{F}_{\mathrm{c}}(\mathcal{Q}_0,\mathcal{R}_0) = \Pr\left\{\bar{\mathcal{Q}}_0 - \tilde{\mathrm{U}}^{(0)}\left(P^{(0)}\right) \le \mathrm{I}_{\mathrm{agg}}\left(P^{(0)}\right) \le \gamma\tilde{\mathrm{U}}^{(0)}\left(P^{(0)}\right) - \sigma_{\mathrm{NC}}^2\right\} \tag{48}$$

where $\tilde{\mathrm{U}}^{(0)} = \tilde{\mathrm{U}}^{(0)}\left(P^{(0)}\right) = \left\{\mathrm{U}^{(0)}\middle|\,\mathrm{U}^{(0)} \ge \tilde{\mathcal{Q}}_0\right\}$ and $\tilde{\mathcal{Q}}_0 = \left(\bar{\mathcal{Q}}_0 + \sigma_{\mathrm{NC}}^2\right)/(\gamma+1)$.

Similar to [51, Eq. (23)], (48) can be formulated in terms of the CDF of $\mathrm{I}_{\mathrm{agg}}$, as follows:

$$\begin{aligned}\mathcal{F}_{\mathrm{c}}(\mathcal{Q}_0,\mathcal{R}_0) &= \mathbb{E}_{P^{(0)}}\left\{F_{\mathrm{I}_{\mathrm{agg}}}\left(\gamma\tilde{\mathrm{U}}^{(0)}\left(P^{(0)}\right) - \sigma_{\mathrm{NC}}^2\middle|\,P^{(0)}\right) - F_{\mathrm{I}_{\mathrm{agg}}}\left(\bar{\mathcal{Q}}_0 - \tilde{\mathrm{U}}^{(0)}\left(P^{(0)}\right)\middle|\,P^{(0)}\right)\right\}\\ &\overset{(a)}{=} \int_0^{\mathcal{M}} F_{\mathrm{I}_{\mathrm{agg}}}\left(\gamma\mathrm{P}G^{(0)}/x - \sigma_{\mathrm{NC}}^2\right) f_{P^{(0)}}(x)\,dx - \int_0^{\mathcal{M}} F_{\mathrm{I}_{\mathrm{agg}}}\left(\bar{\mathrm{Q}}_0 - \gamma\mathrm{P}G^{(0)}/x\right) f_{P^{(0)}}(x)\,dx\end{aligned} \tag{49}$$

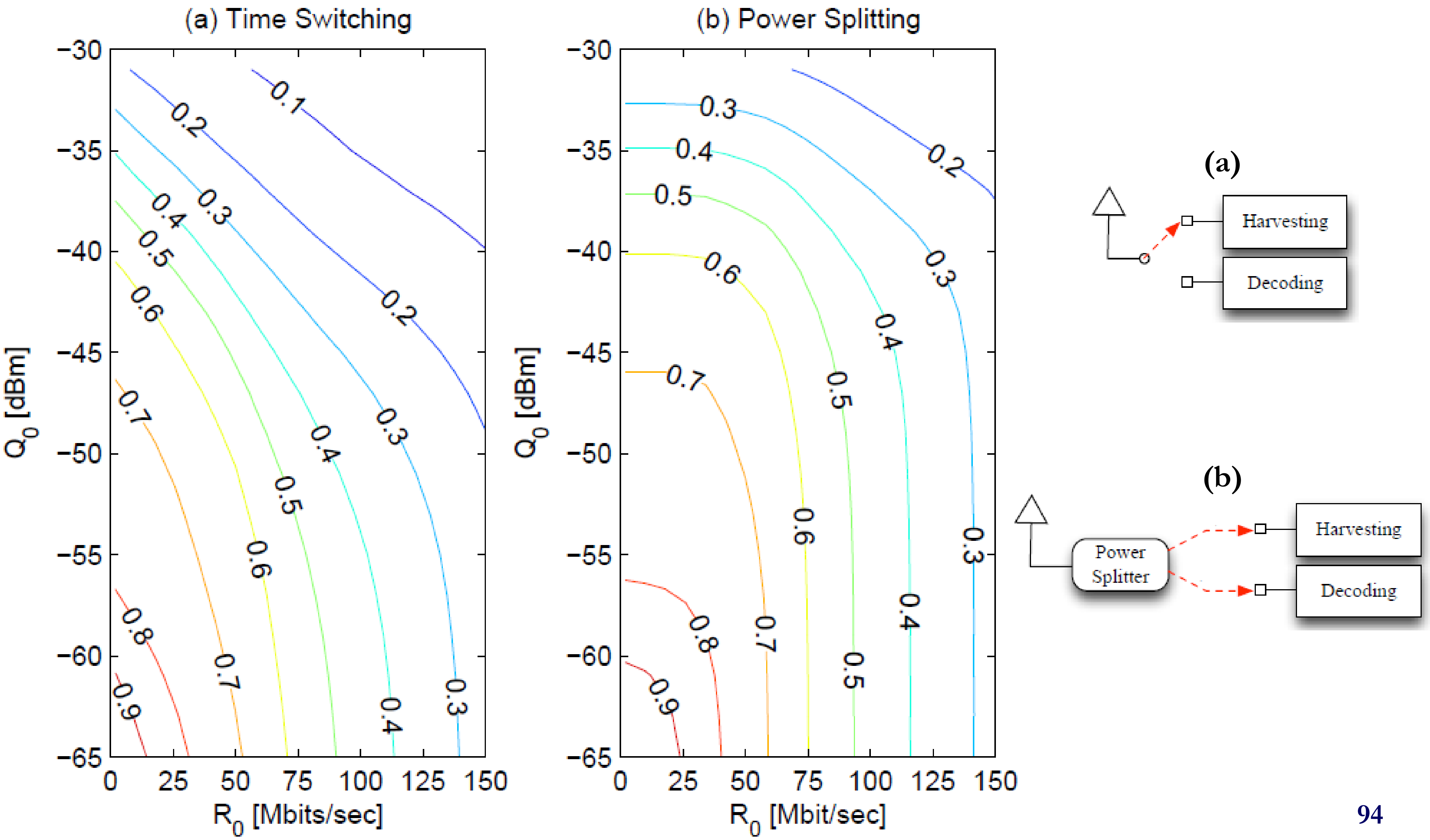
where (a) originates from the fact that the condition $\mathrm{U}^{(0)} \ge \tilde{\mathcal{Q}}_0$ implies $P^{(0)} \le \mathrm{P}G^{(0)}\tilde{\mathcal{Q}}_0^{-1} = \mathcal{M}$.

The rest of the proof follows by rewriting the CDF of $\mathrm{I}_{\mathrm{agg}}$ in (49) in terms of its CF, $\Phi_{\mathrm{I}_{\mathrm{agg}}}^{(\mathrm{RP})}\left(\cdot\middle|\,P^{(0)}\right)$, and by invoking the Gil-Pelaez inversion theorem [68]. In particular, $\Phi_{\mathrm{I}_{\mathrm{agg}}}^{(\mathrm{RP})}\left(\cdot\middle|\,P^{(0)}\right)$ is available in *Lemma 4* in an approximate closed-form. Some algebraic manipulations lead to the final result.

M. Di Renzo and W. Lu, "System-Level Analysis of Cellular Networks with Simultaneous Wireless Information and Power Transfer: Stochastic Geometry Modeling", IEEE Trans. Vehicular Technol., IEEE Early Access.

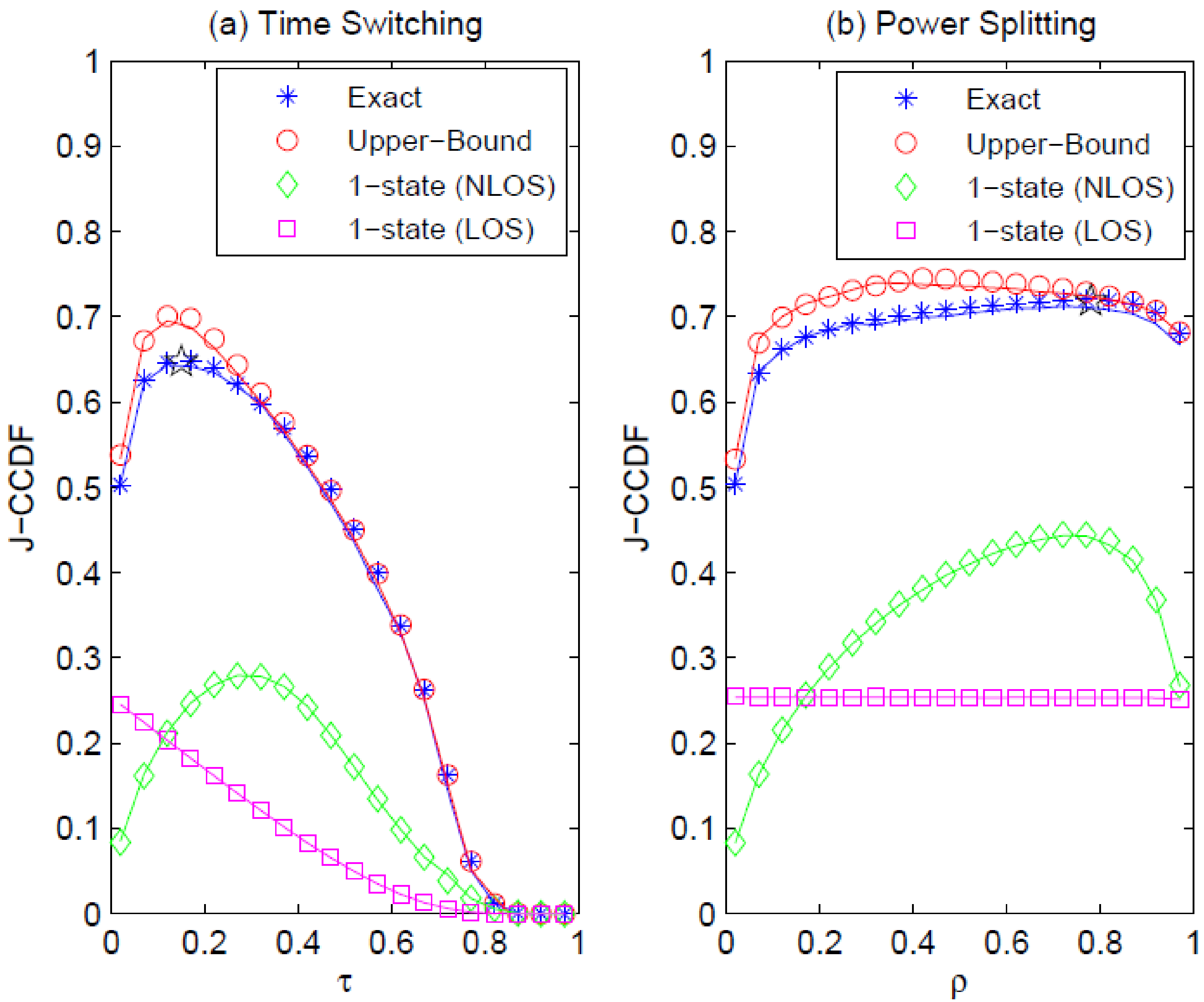
SWIPT – Trends and Insight

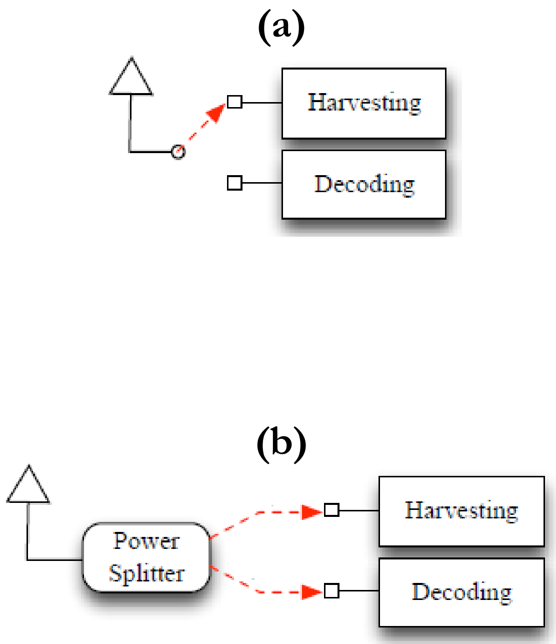
Feasibility Regions: Rate and Energy Targets are BOTH Achieved



SWIPT – Trends and Insight

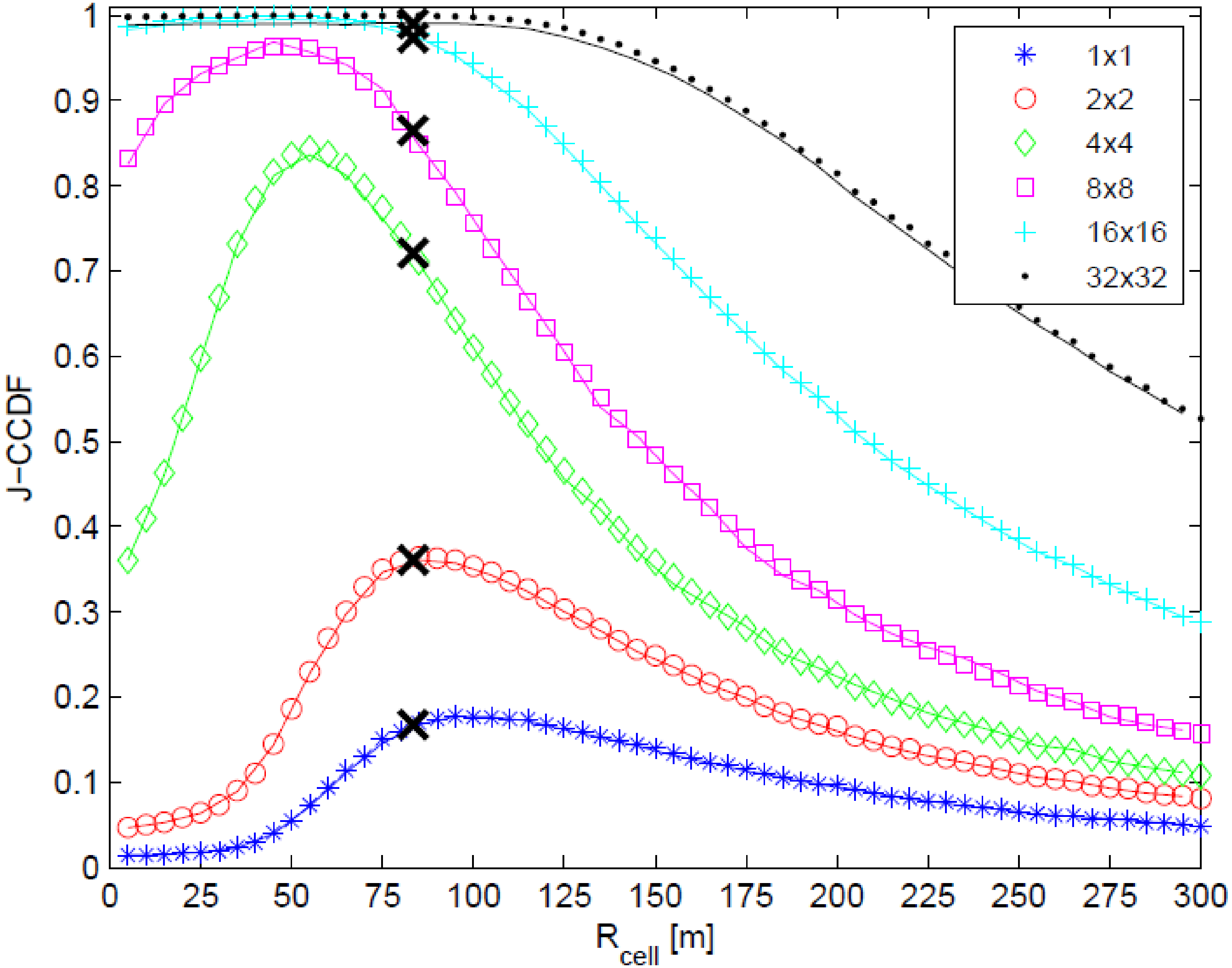
System-Level Optimization & Importance of Channel Modeling



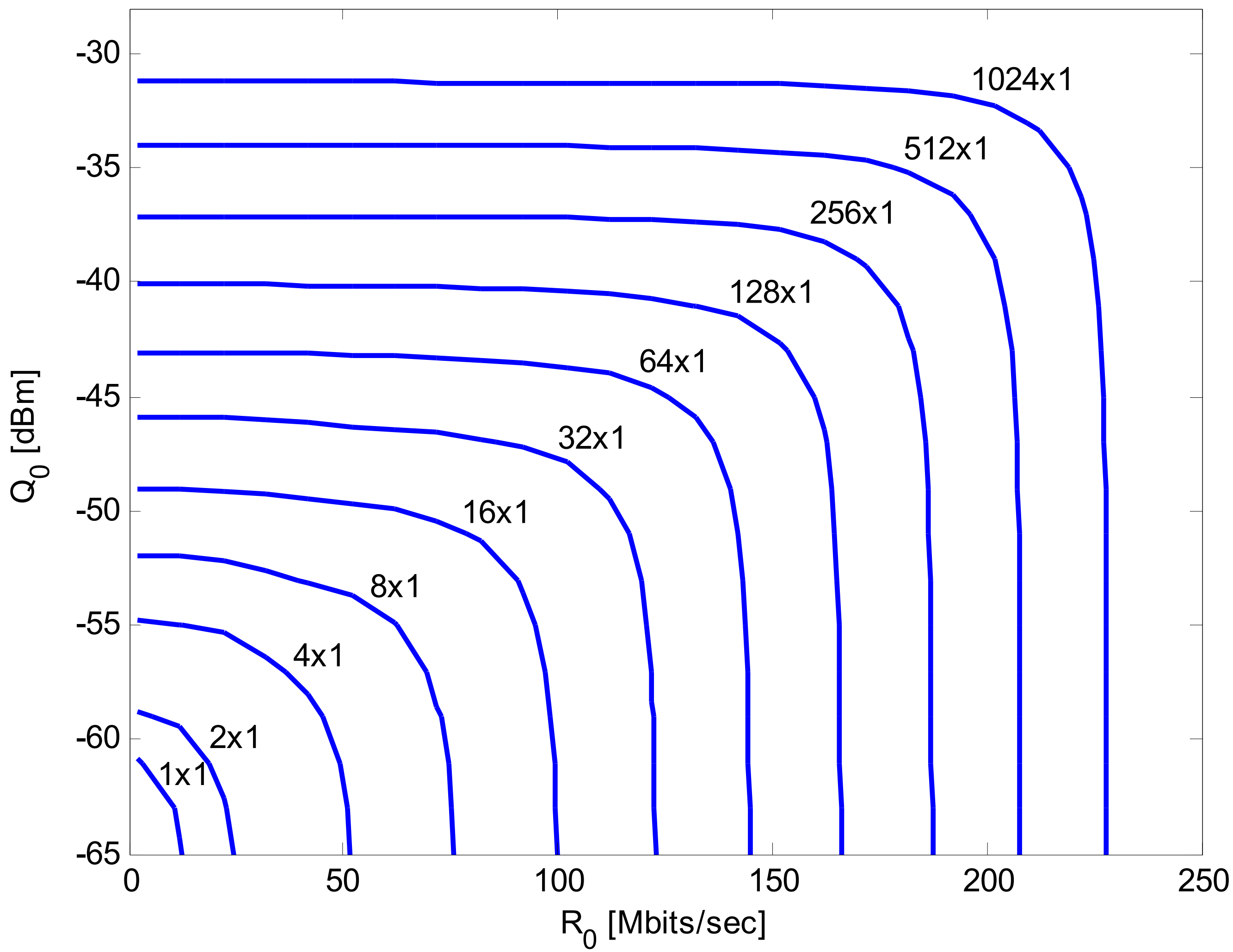


SWIPT – Trends and Insight

Impact of Cellular Network Density: Network Densification

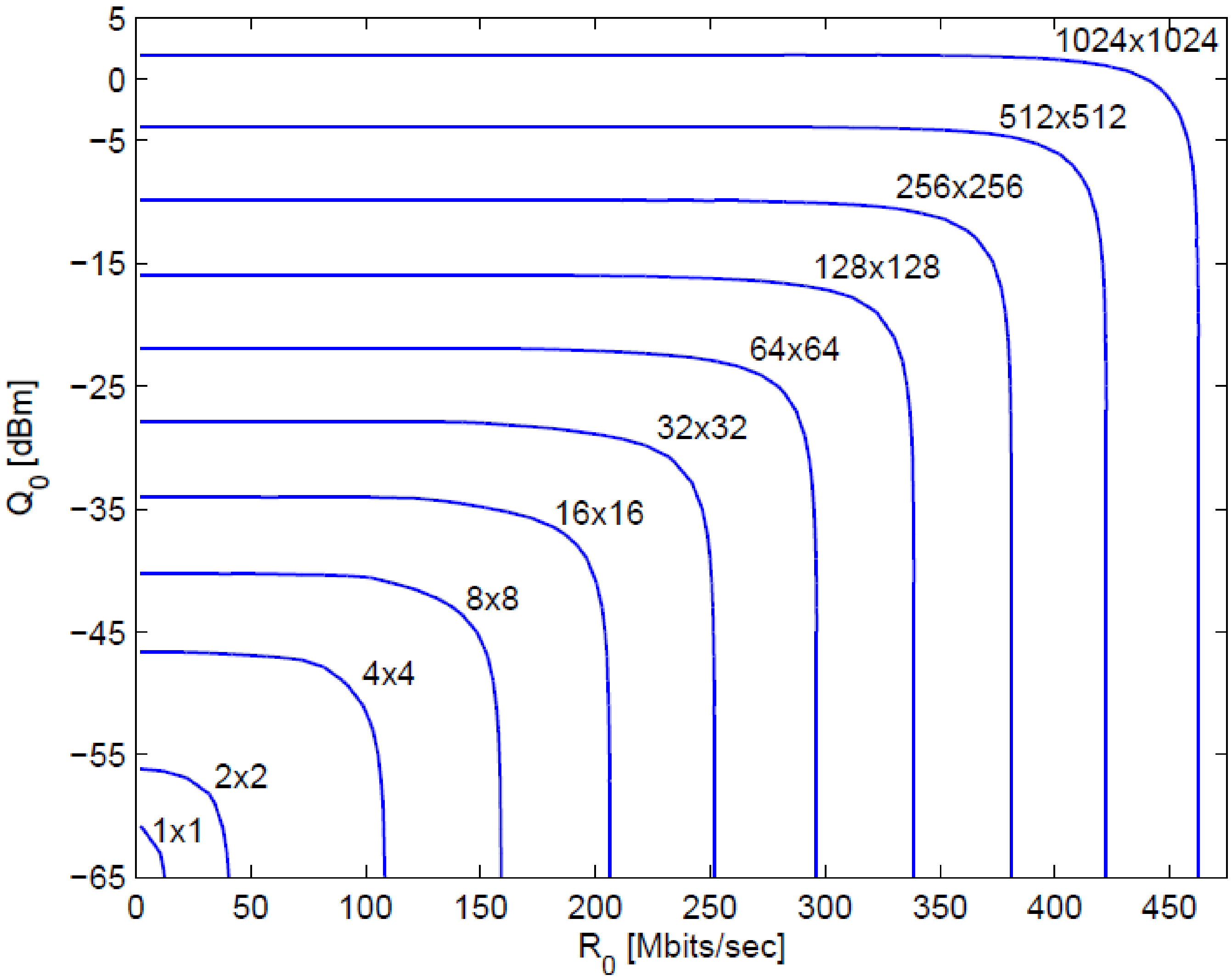


Impact of Multi-Antenna Transmission: Massive MIMO



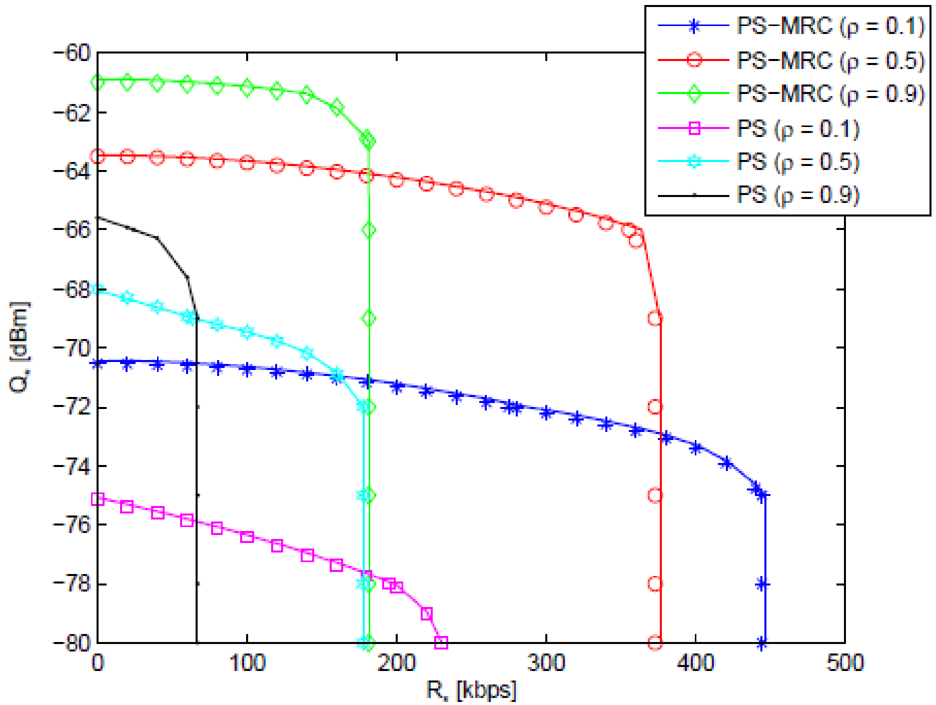
SWIPT – Trends and Insight

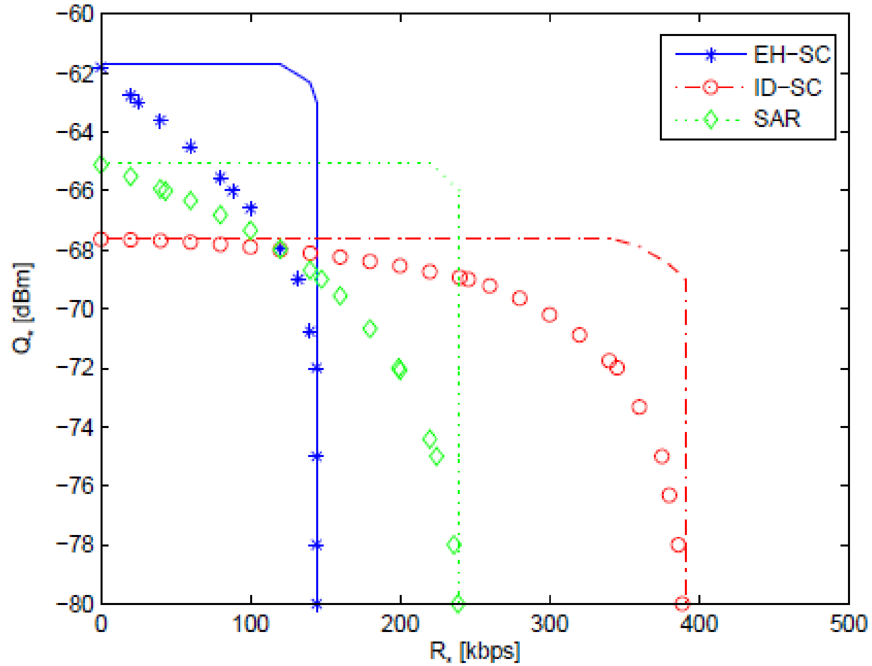
Impact of Multi-Antenna Transmission: Massive MIMO



SWIPT – If The Receiver is NOT Adaptive

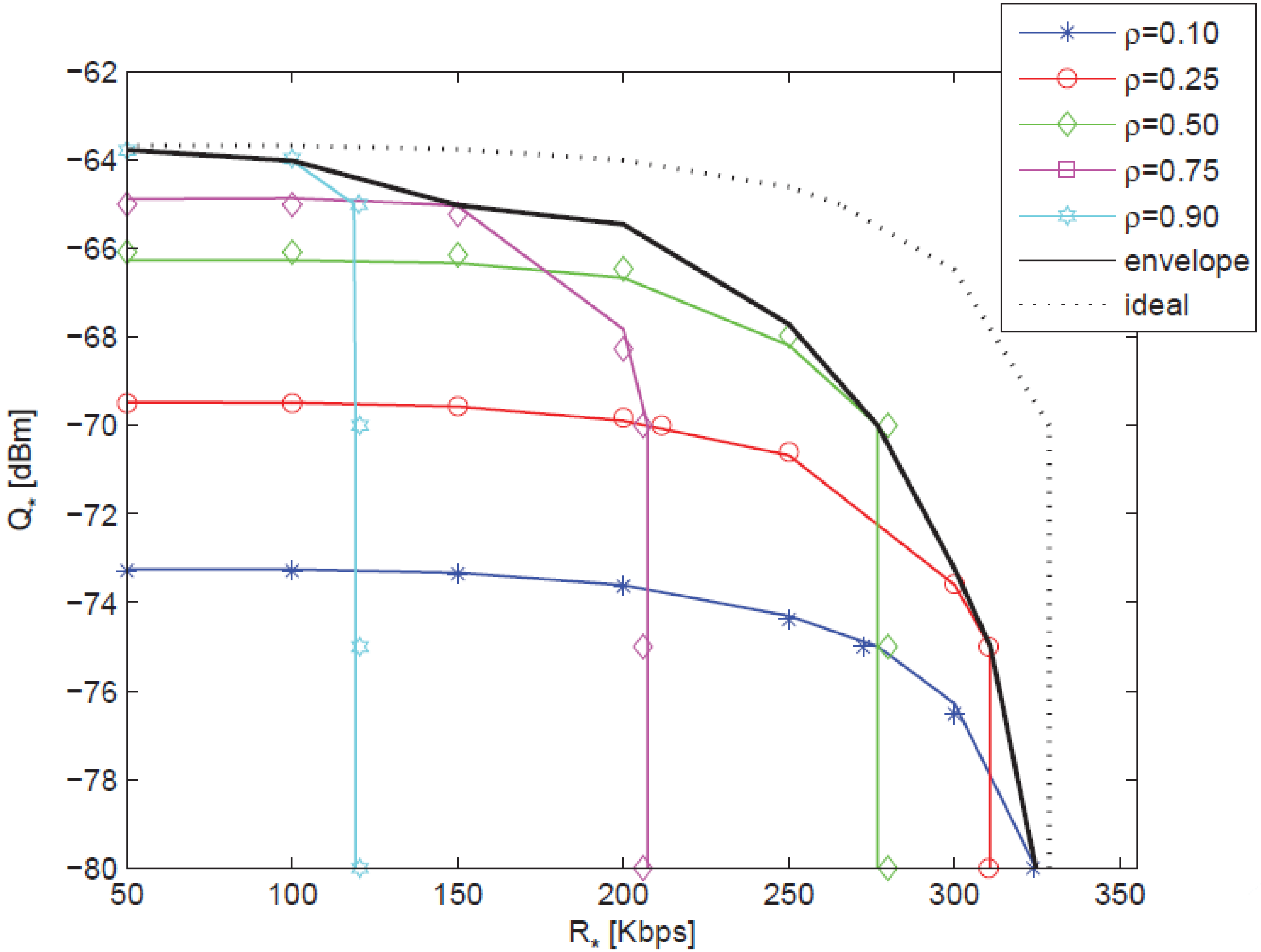
Impact of Parameter Setups: Two Receive Antennas (MRC, SC)





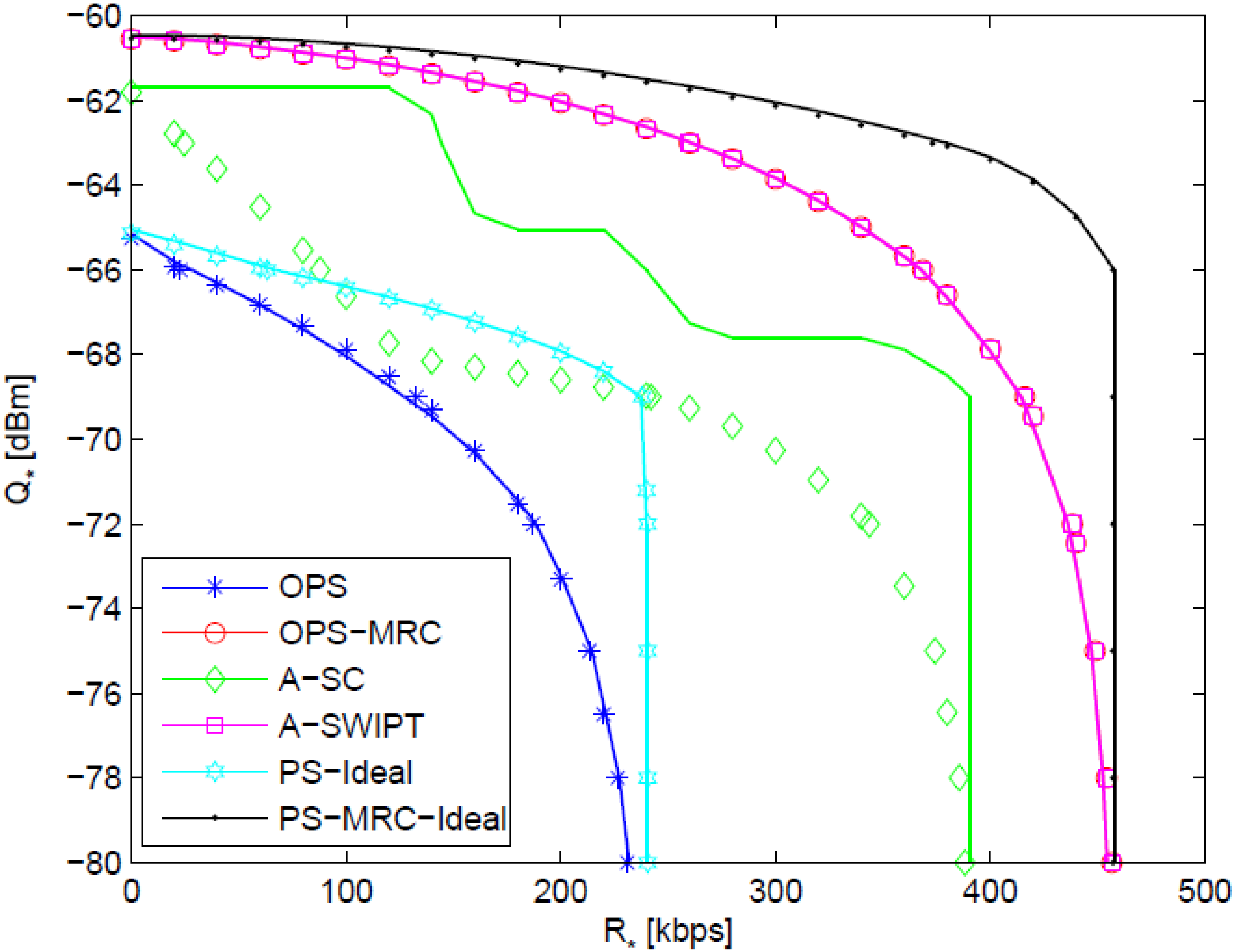
SWIPT – If The Receiver is Adaptive

Impact of Parameter Setups: Adaptation as a function of ϱ

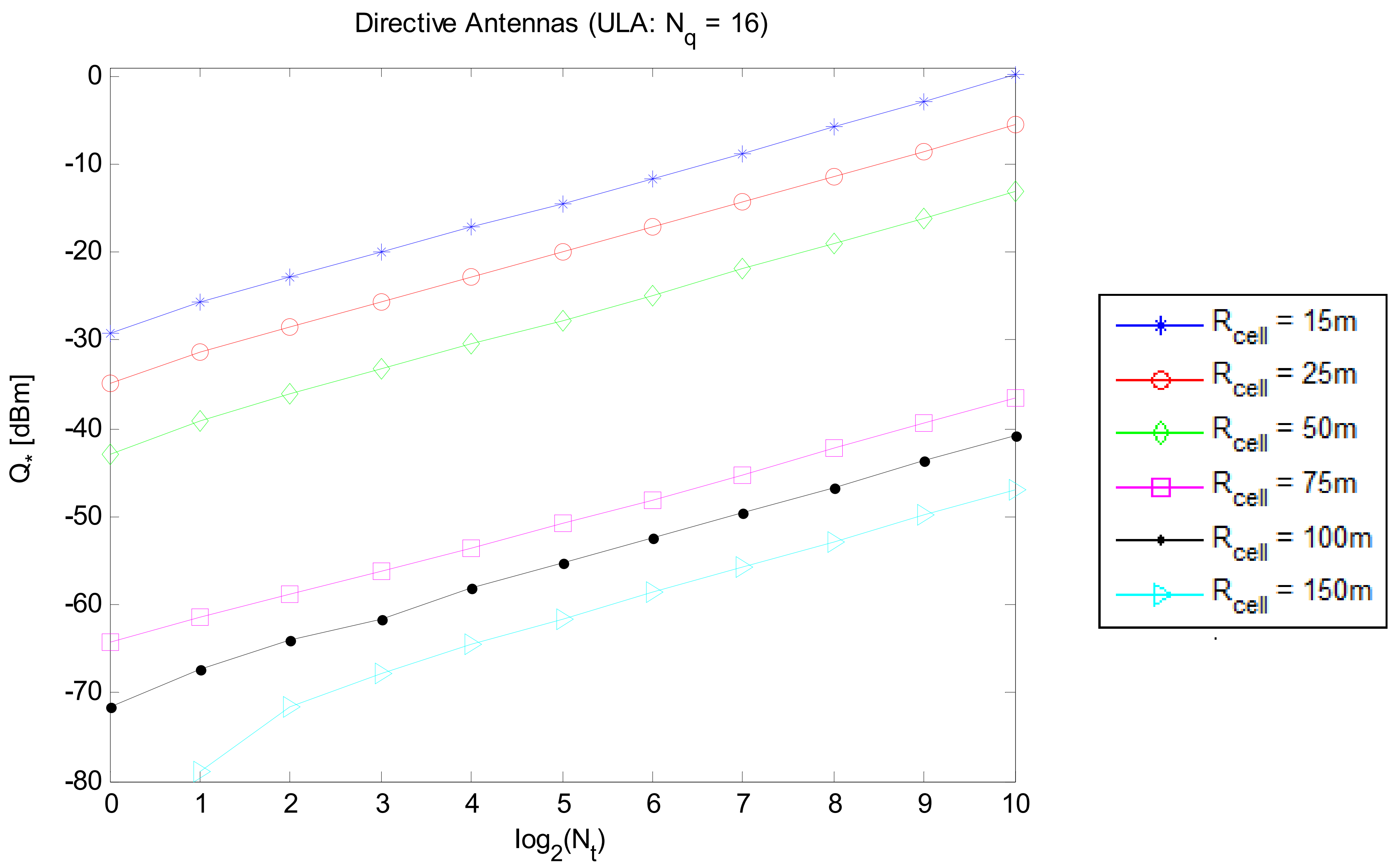


SWIPT – If The Receiver is Adaptive

Impact of Parameter Setups: Two Receive Antennas (MRC, SC)



SWIPT – How Much Power Can We Harvest?



SWIPT – Main Takes

- **Takeaway messages for system-level analysis (proofs in the paper):**
  - **Optima power splitting and time switching ratios exist and are unique**
  - **Power splitting outperforms time switching if they operate at their respective optima**
  - **Impact of directional beamforming: reducing the other-cell interference leads to the optimum**
  - **Impact of base stations density: existence of an optimal deployment density**
  - **Wireless power transfer: Densification of base stations and antennas is mandatory for (possibly) making it a reality → Energy-Neutral design**

Design Rule

Network densification: To bring the access points closer to the users

Directional beamforming: To reduce the other-cell interference generated by network densification and to enhance the power gain of the intended link

The System-Level Side of 5G – YouTube Video

https://youtu.be/MB8IvOYYvB0

Some Reference Papers…

- M. Di Renzo and W. Lu, "System-Level Analysis/Optimization of Cellular Networks with Simultaneous Wireless Information and Power Transfer: Stochastic Geometry Modeling", IEEE Trans. Vehicular Technol., IEEE Early Access.
- Y. Deng, L. Wang, M. Elkashlan, M. Di Renzo, and J. Yuan, "Modeling and Analysis of Wireless Power Transfer in Heterogeneous Cellular Networks", IEEE Trans. Commun., IEEE Early Access.
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- W. Lu, M. Di Renzo, and T. Q. Duong, "On Stochastic Geometry Analysis and Optimization of Wireless-Powered Cellular Networks", IEEE GLOBECOM, Dec. 2015.
- T. Tu Lam, M. Di Renzo, and J. P. Coon, "MIMO Cellular Networks with Simultaneous Wireless Information and Power Transfer", IEEE SPAWC, July 2016.

Thank You for Your Attention

- **ETN-5Gwireless (H2020-MCSA, grant 641985)**

  An European Training Network on 5G Wireless Networks

  http://cordis.europa.eu/project/rcn/193871_en.html (Jan. 2015, 4 years)

5Gwireless

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