Outline of the Talk

A brief introduction

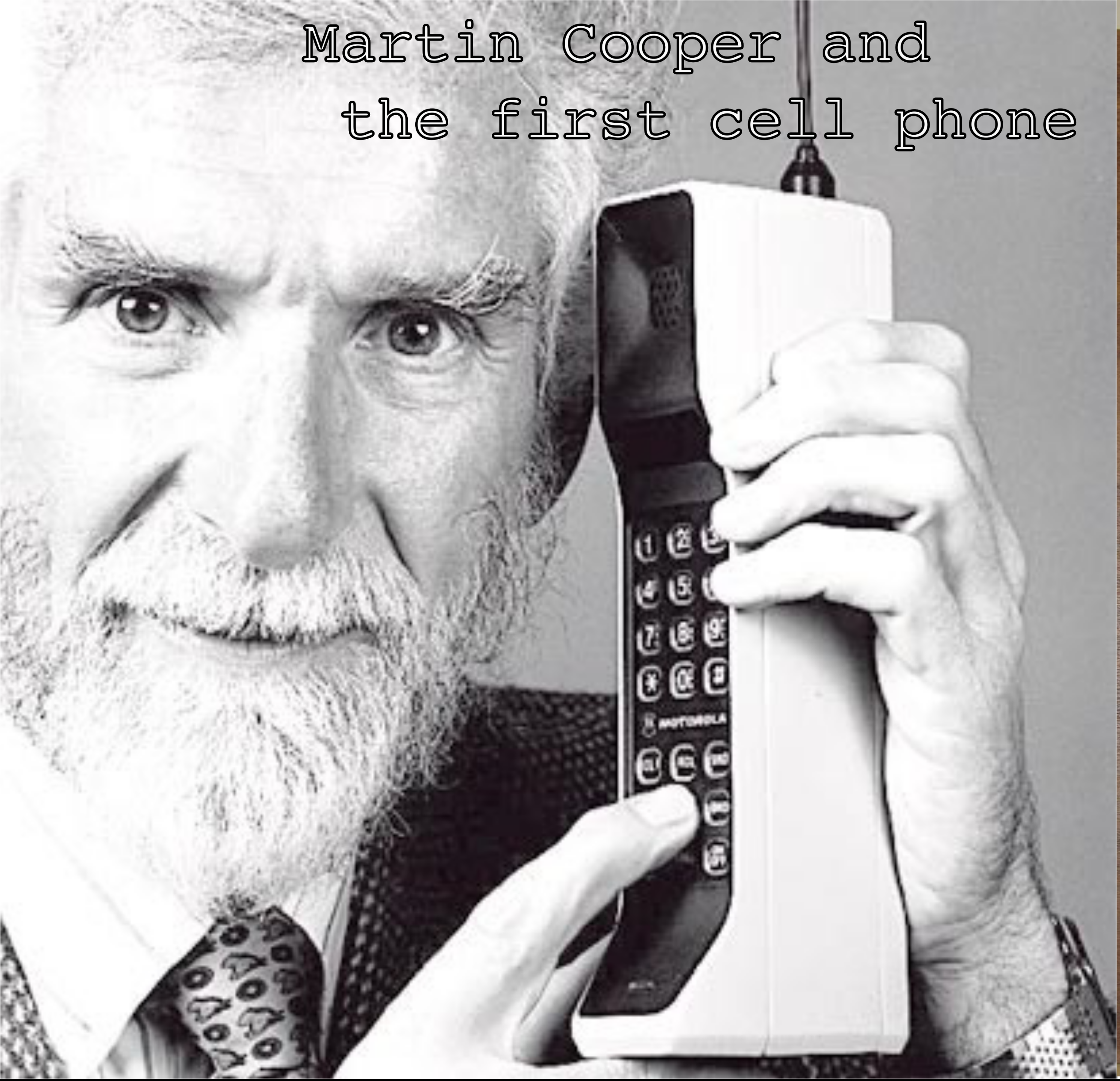
Resource allocation examples

Tilt angle of the base station antennas

LTE and Wi-Fi user association

Small cells sleep mode scheduling

A forward looking remarks


Martin Cooper and the first cell phone


A radio phone for first cellular operator in Germany

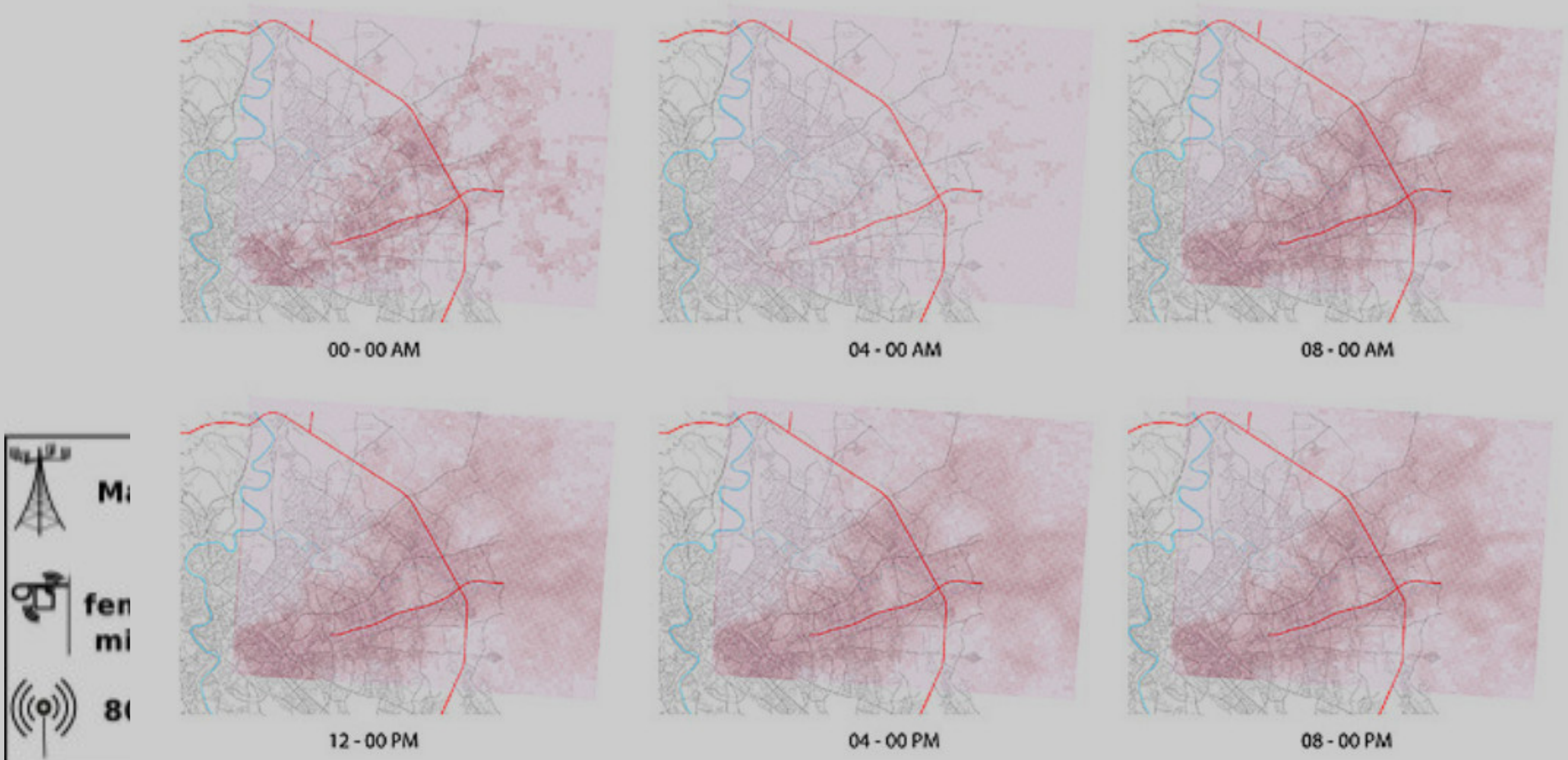
Today

3.7 billion LTE subscribers alone by the end of 2020

Cellular networks are becoming more complex

SO, a new challange has arised for the mobile operator

Architecture and Demand Variations

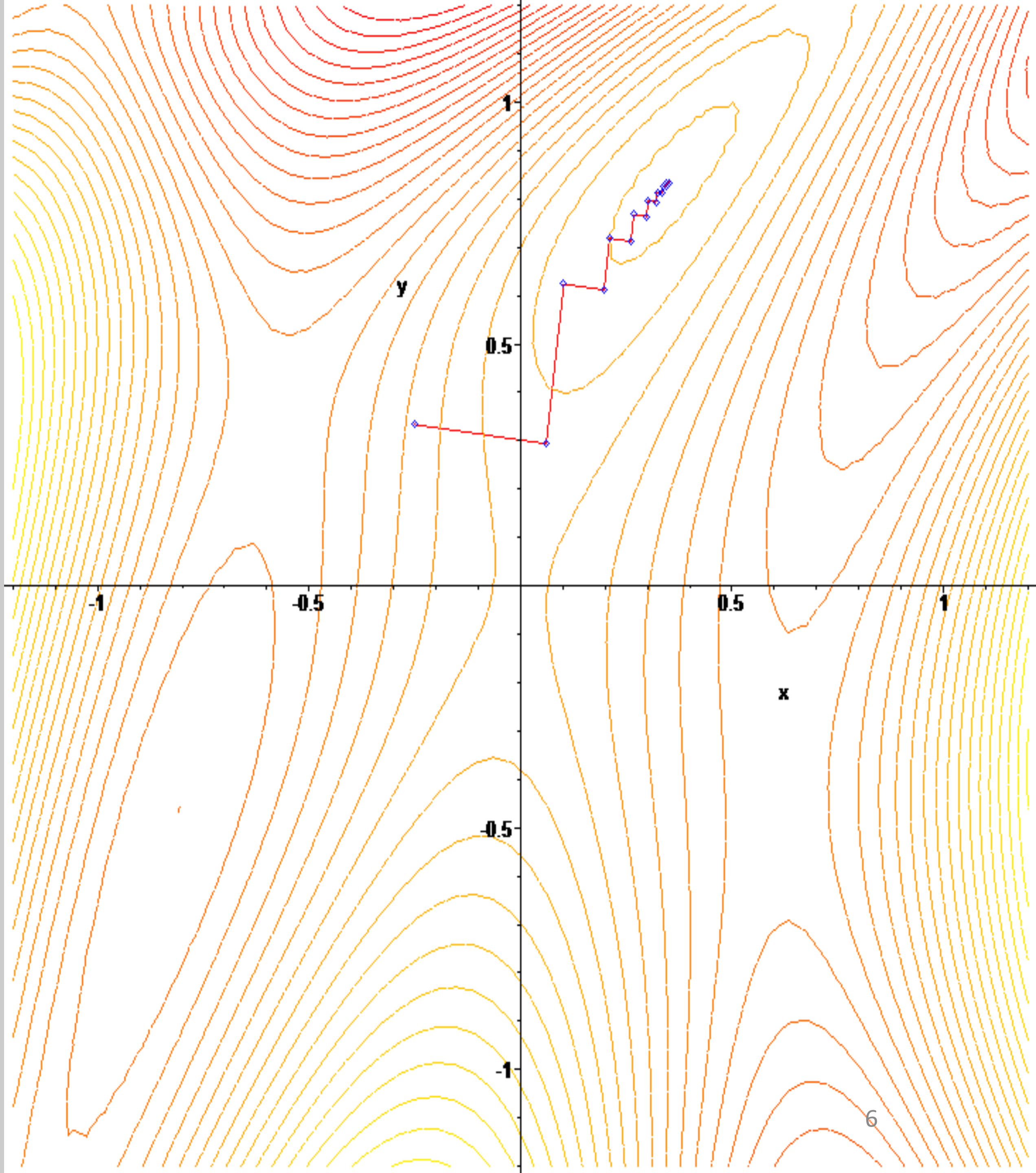


Fundamental Questions:

Which **utility metric** to choose?

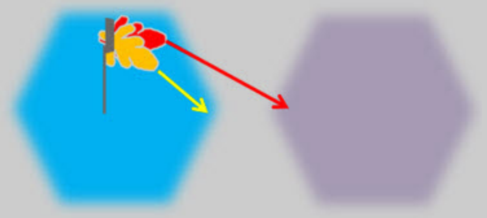
What resources are most valuable?

Are our solutions **scalable**, what are implementation implications?



Problem:

Co-channel LTE base stations operate on same frequency bands.



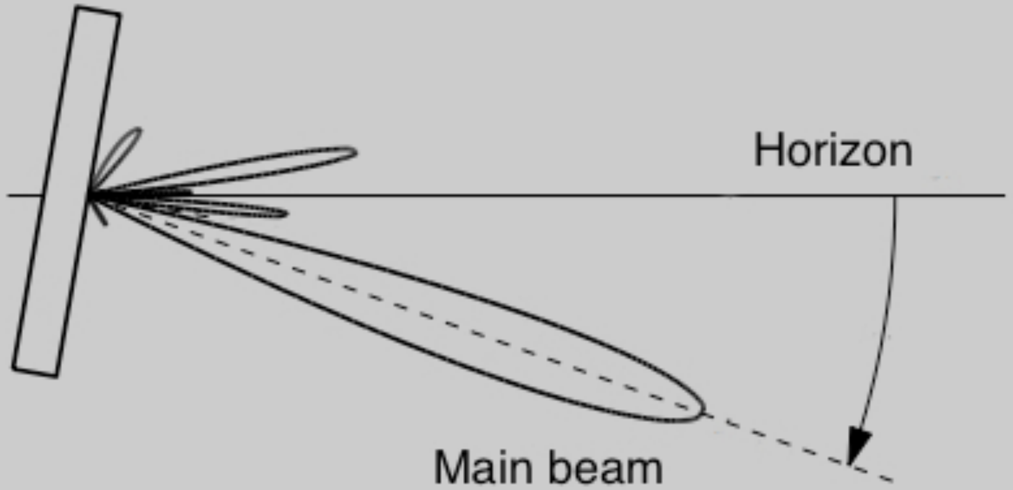
Users of neighboring BSs suffer from **interference**.

$$\gamma_u^i(\overset{\text{Tilt angles}}{\boxed{\Theta}}) = \frac{P_{R,u}(\theta_{b(u)})}{\underbrace{\boxed{\sum_{c \in \mathcal{B} \setminus \{b(u)\}} \hat{P}_{R,u}(c)}}_{\text{Interference}} + \sigma_n^2}$$

What is a simple way to maximize network utility (*e.g.* sum log **rate**)?

$$r_u(\Theta) = \frac{\beta_1 \omega}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \log(1 + \gamma_u^i(\Theta)/\beta_2)$$

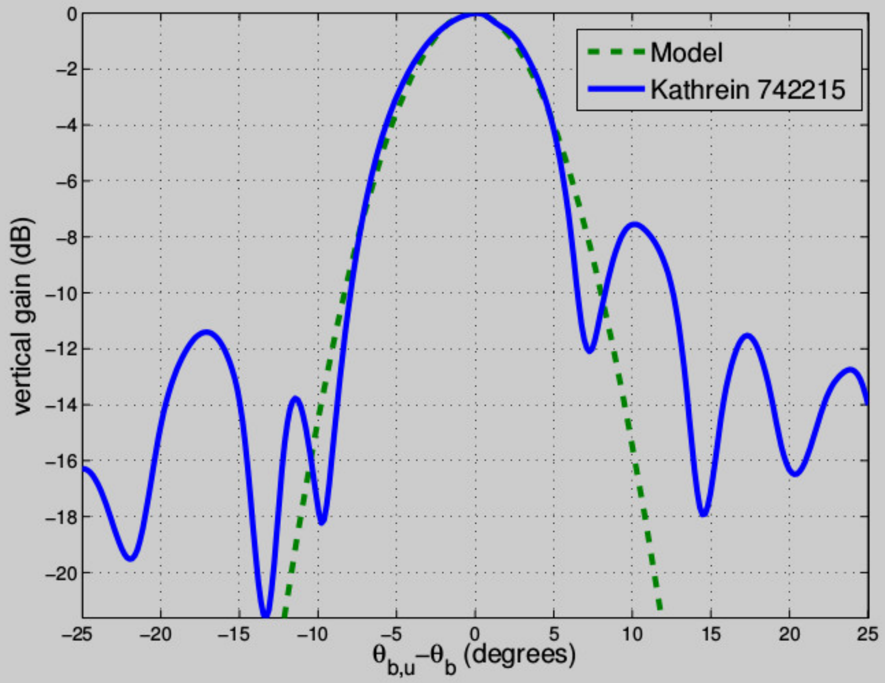
Interference depends on the received powers



Received powers depend on the gain of the antennas

$$\tilde{G}_{b,u}(\theta_b) = \tilde{G}_0 \tilde{G}_v(\theta_b, d_{b,u})$$

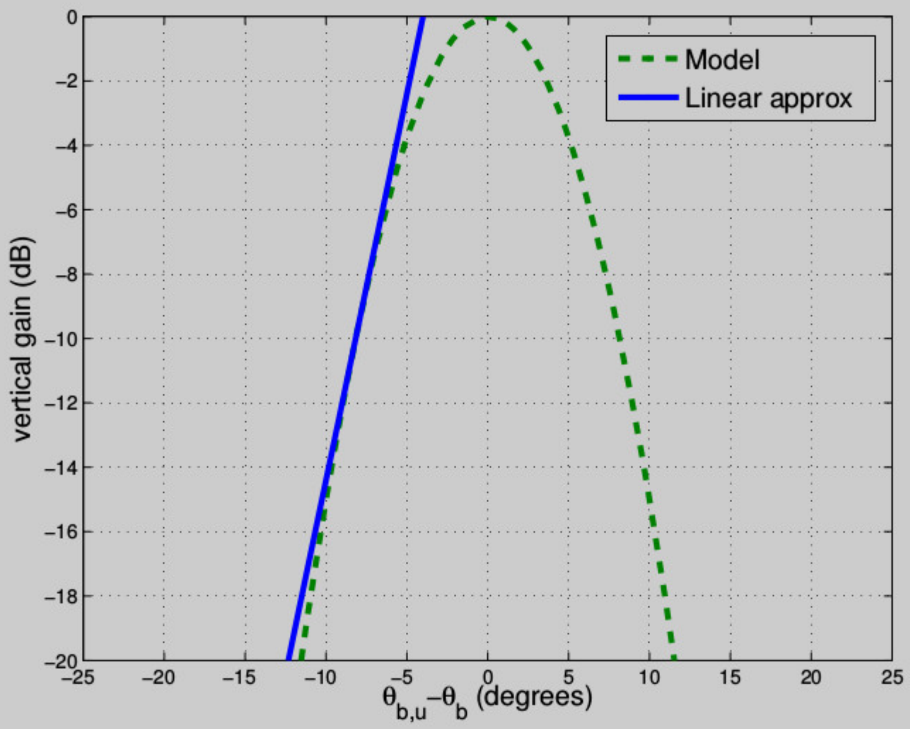
$$\tilde{G}_v(\theta_b, d_{b,u}) = 10^{-1.2\left(\frac{\theta_{b,u}-\theta_b}{\theta_{3dB}}\right)^2}$$



Objective becomes a complex function of tilt angles!

$$r_u(\Theta) = \frac{\beta_1 \omega}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \log(1 + \gamma_u^i(\Theta)/\beta_2)$$

Is it time to give up and try heuristics?



Convexity

Lemma 0.1 $h(x) = \log(\log(1 + e^x))$ *is concave and non-decreasing in* $x \in \mathcal{R}$.

Lemma 0.2 $\log(r_u(\Theta))$ *is concave in* Θ.

$$\log(r_u(\Theta)) = \frac{\beta_1 \omega}{|\mathcal{I}|} \sum_{i \in |\mathcal{I}|} \log(\log(1 + \gamma_u^i(\Theta)/\beta_2) = \frac{\beta_1 \omega}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \log(\log(1 + e^{\hat{r}^i_u(\Theta)}))$$

Conventional solution approach:

Lagrangian and KKT conditions

$$L(\Theta, \Lambda) = -\sum_{u \in \mathcal{U}} \log r_u(\Theta) + \sum_{u \in \mathcal{U}} \lambda_u^1 (\log \underline{r} - \log r_u(\Theta)) + \sum_{b \in \mathcal{B}} \lambda_b^2 (\underline{\theta} - \theta_b) + \sum_{b \in \mathcal{B}} \lambda_b^3 (\theta_b - \bar{\theta})$$

Main KKT conditions are

$$\sum_{u \in \mathcal{U}} \left(1 + \lambda_u^1\right) \partial_{\theta_b} U(r_u(\Theta)) = \lambda_b^3 - \lambda_b^2, \quad b \in \mathcal{B}$$

However solving this equation, imposes complex dual constraints for a solution to exit.

A different approach: Light-weight Distributed algorithm

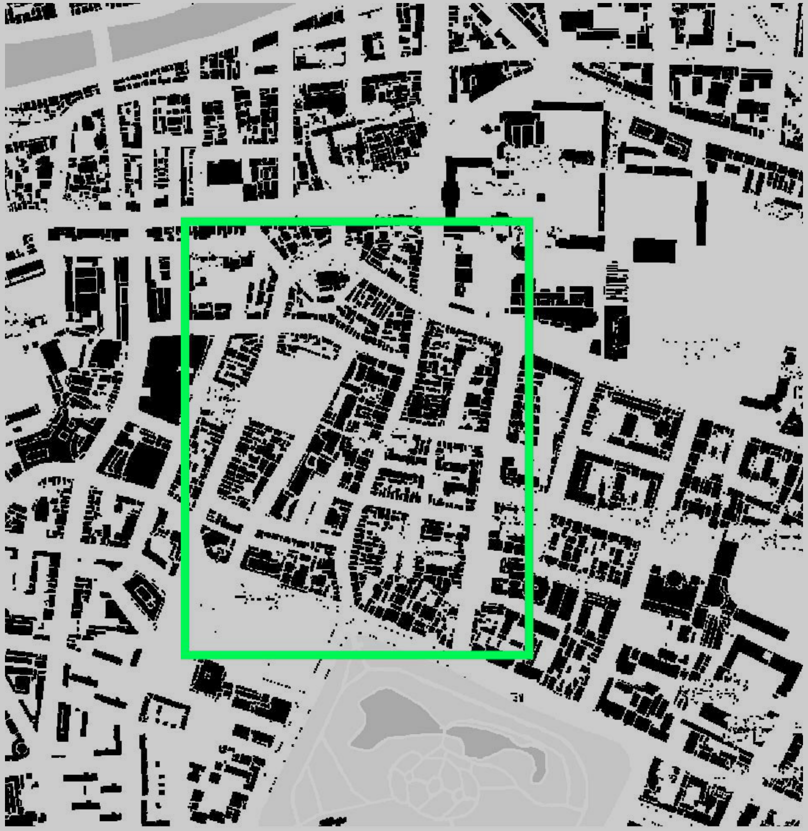
$$
\begin{aligned}
&\textbf{Initialise}: t = 0, \Theta(0), \Lambda(0), \textbf{step size } \alpha > 0\\
&\textbf{do}\\
&\quad \theta_b(t+1) = \theta_b(t) - \alpha \partial_{\theta_b} L(\Theta(t), \Lambda(t)), \qquad \theta_b \in \mathcal{B}\\
&\quad \lambda_u^1(t+1) = \left[\lambda_u^1(t) + \alpha \partial_{\lambda_u^1} L(\Theta(t), \Lambda(t))\right]^+, \; u \in \mathcal{U}\\
&\quad \lambda_b^i(t+1) = \left[\lambda_b^i(t) + \alpha \partial_{\lambda_b^i} L(\Theta(t), \Lambda(t))\right]^+, \; b \in \mathcal{B}, i = 2, 3\\
&\quad t \leftarrow t+1\\
&\textbf{loop}
\end{aligned}
$$

$\boxed{\partial_x L(\Theta(t), \Lambda(t))}$ Just a sub-gradient of objective and constraints wrt x, easy to compute for the multipliers

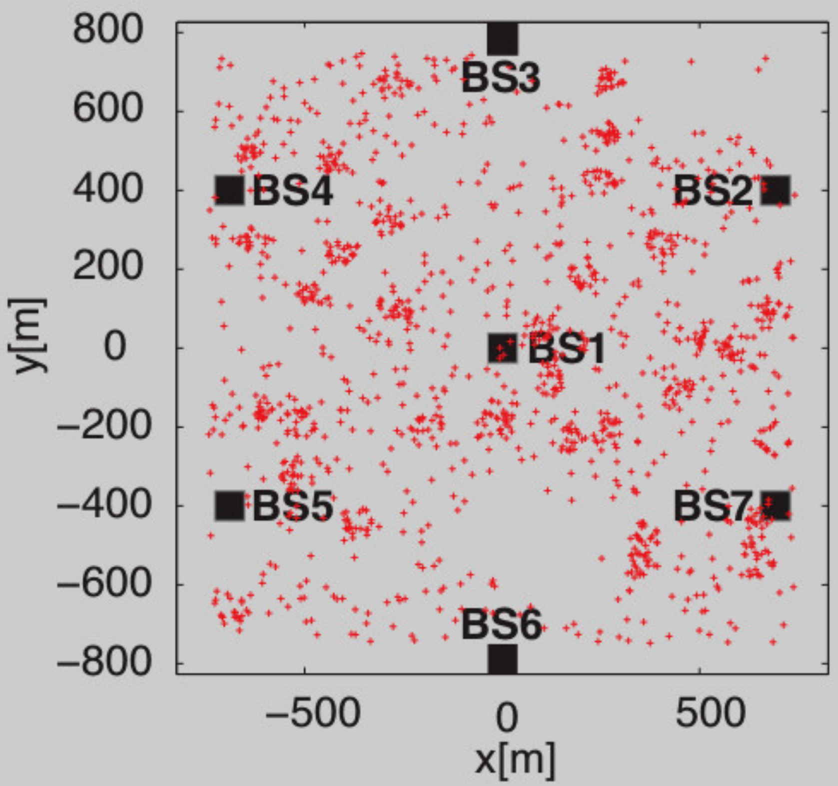
$\boxed{\partial_{\theta_b} L(\Theta(t), \Lambda(t))}$ Requires knowledge of received powers, and SINRS (already recorded at the devices), pointing angle between base station and the user,

The complexity of the algorithm scales linearly with the size of the network

Simulations- Dublin City Center

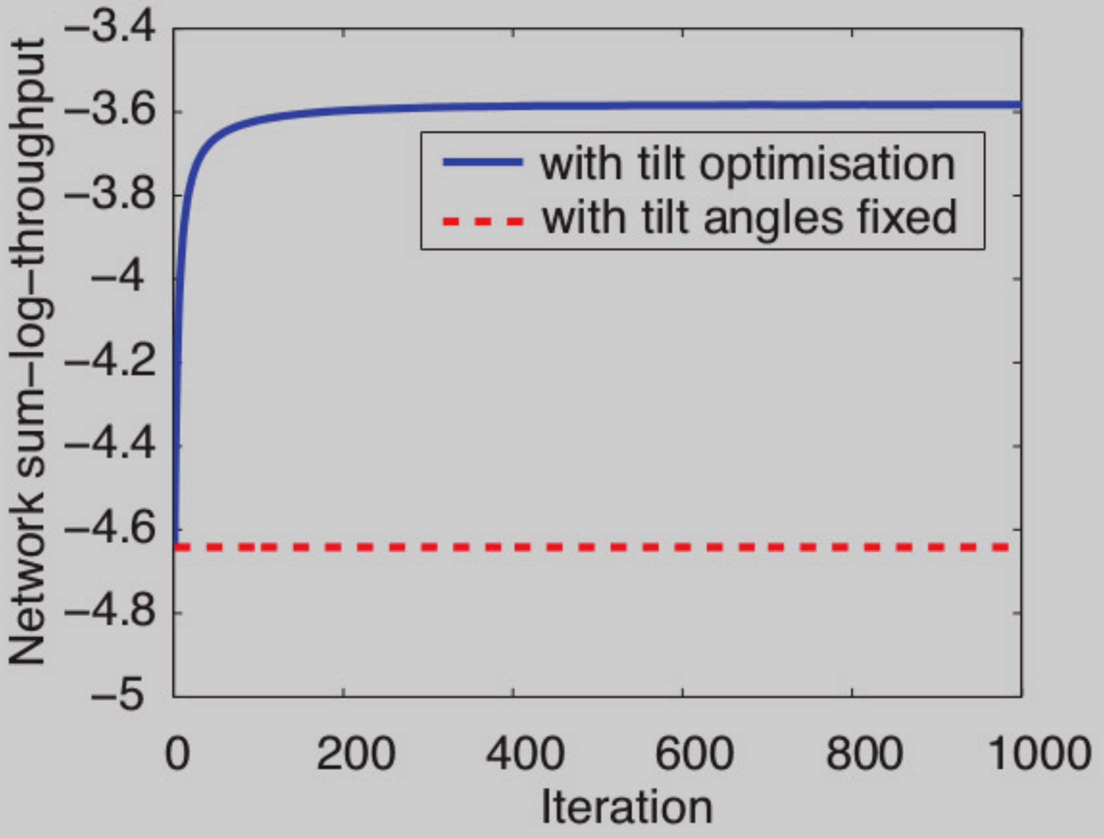


Dublin city center

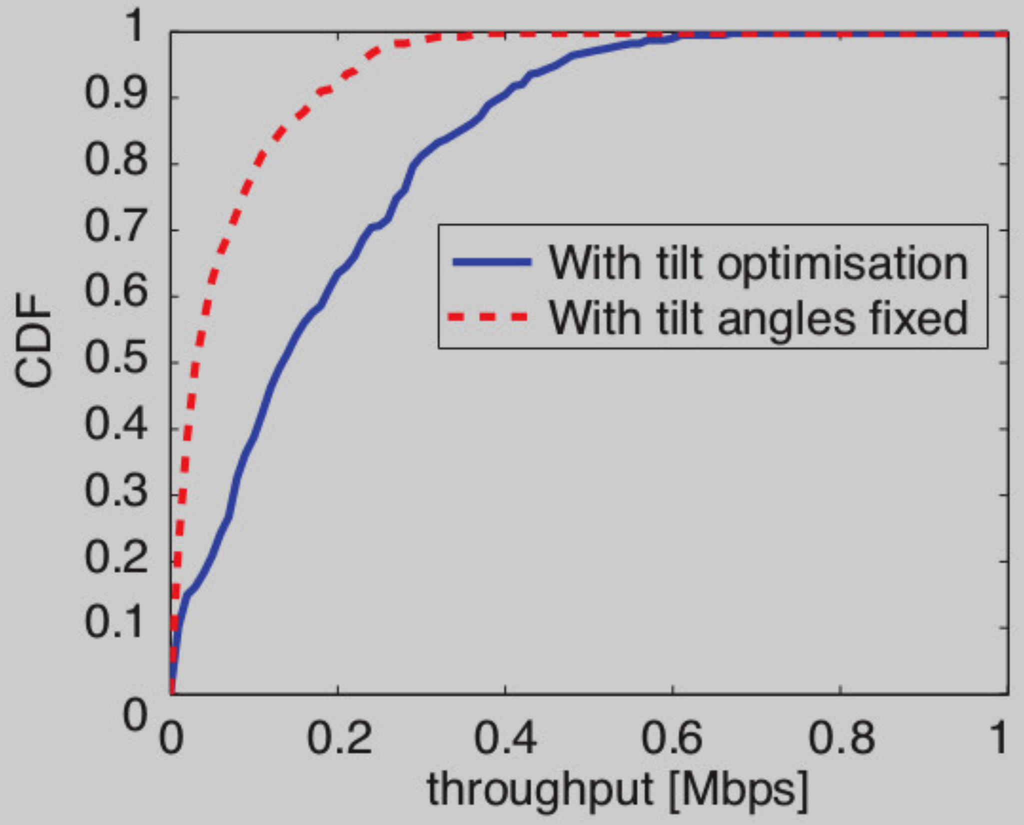


Position of the LTE base station
and the users

Some Results (convergence):



Sum-log-throughputs



CDF of user throughputs

22% improvement in the objective, extended discussions can be found in [1,2]

[1] B. Partov et. al. " Utility Fair Optimization of Antenna Tilt Angles in LTE Networks ", IEEE/ACM Transactions on Networking, Feb 2015

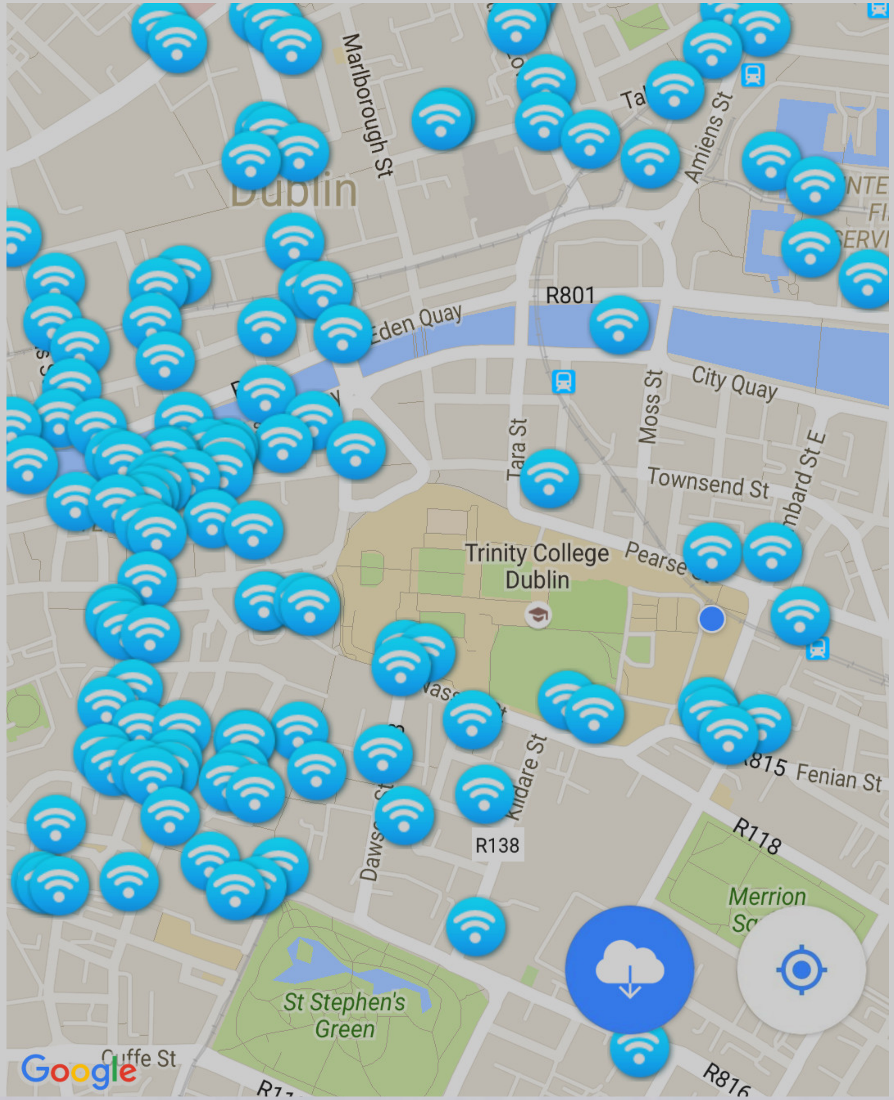
[2] B. Partov et. al. "Tilt Angle Adaptation in LTE Networks with Advanced Interference Mitigation ", IEEE- PIMRC, Sep 2014

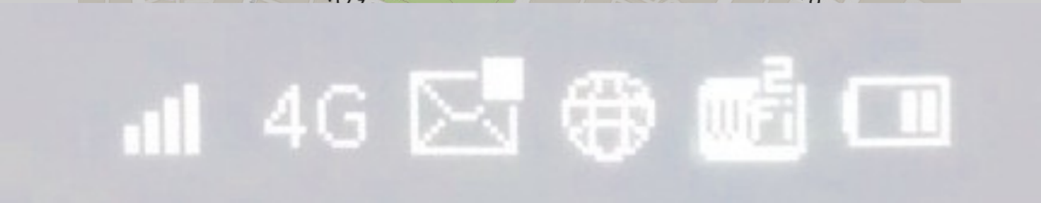
Users and Base stations

Most mobile users have multi-homing capabilities

State of the art: multi-homed users either connect to Wi-Fi or Cellular BSs.
(some multi-path TCP implementations e.g. iPhones)

Question: Schedule users between base stations to maximize network utility
(sum log of the user rates)





Scheduling by Frequency/Time Slotting

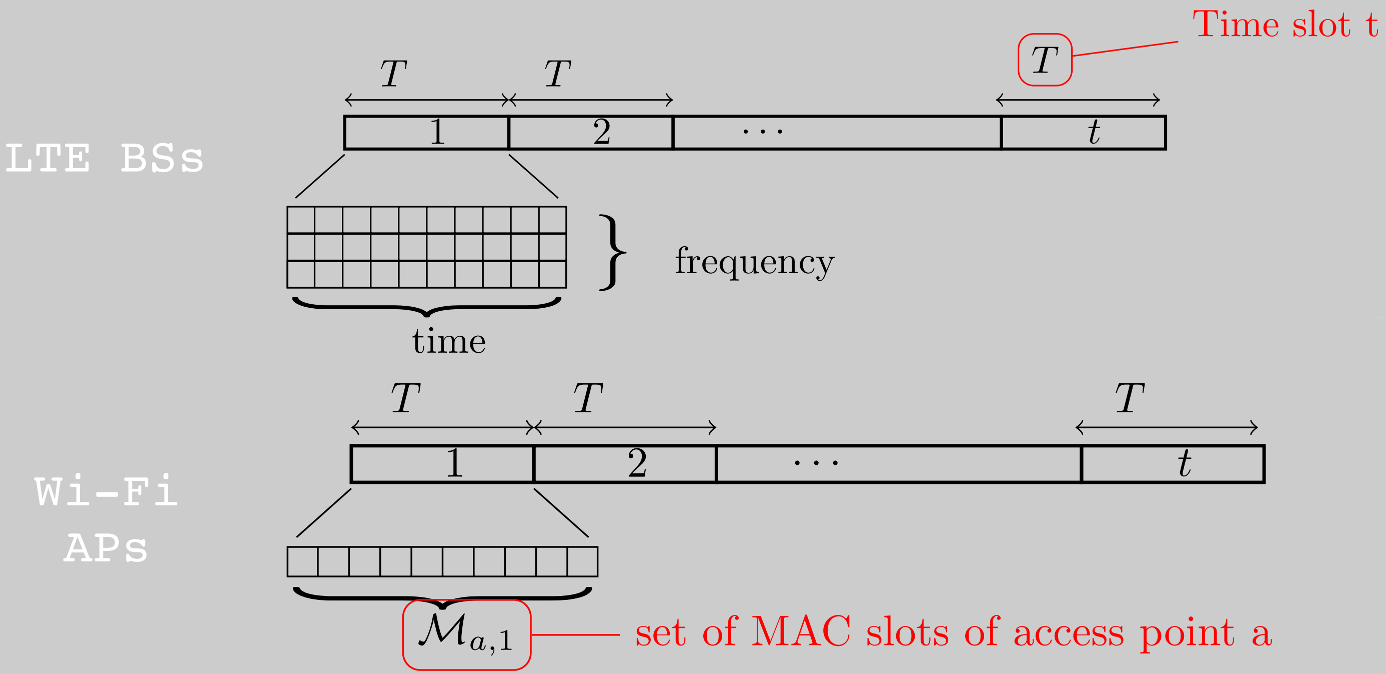
Optimization problem (P)

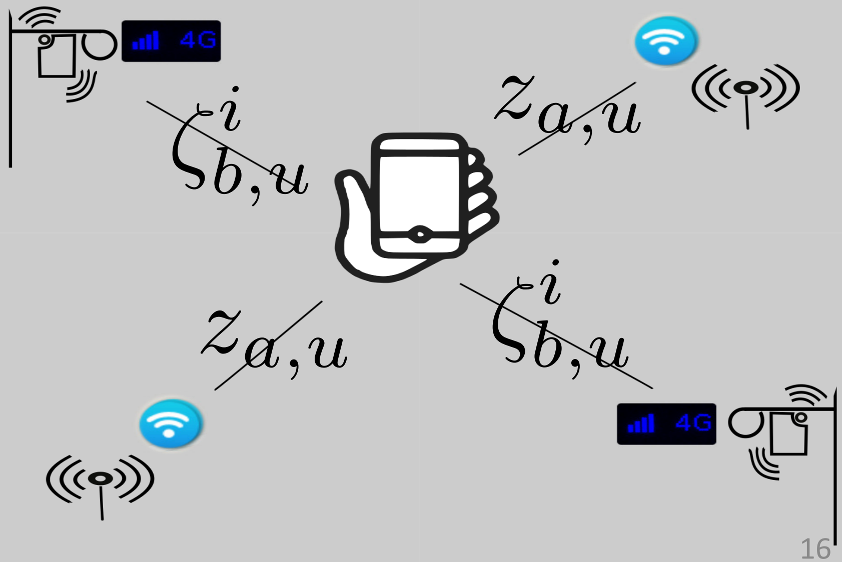
$$\max_{\mathbf{s},\mathbf{r}} \sum_{u\in\mathcal{U}} \log\left(s_u + r_u\right)$$

$$s.t. \quad \mathbf{s} \in \boxed{\hat{\mathcal{R}}_{wifi}}, \quad \mathbf{r} \in \boxed{\mathcal{R}_{lte}}$$

Wi-Fi rate region

LTE rate region

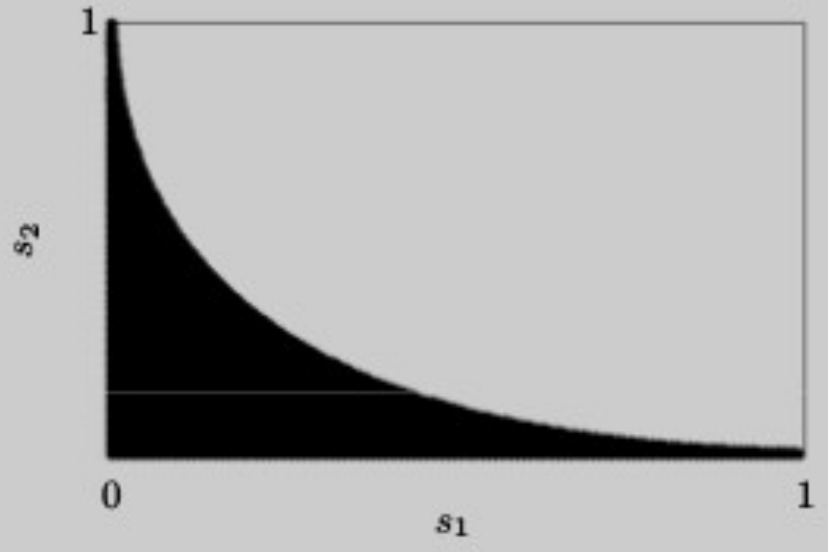




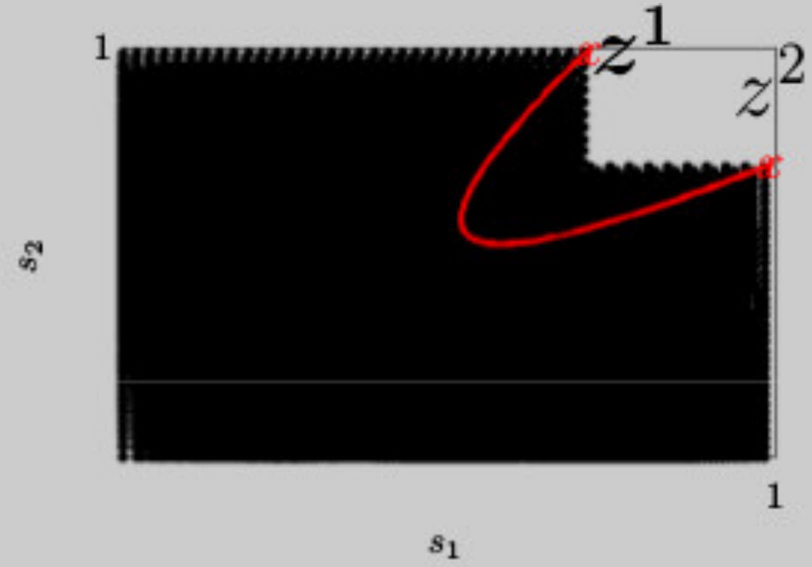
Rate Regions

LTE Rate region is affine in the decision variables

Wi-Fi rate region is more complex



Wi-Fi rate region of two users and one AP



Wi-Fi rate region of two users and two APs

Can we simplify the problem?

Standard form of our optimization problem (P)

$$\min_{\mathbf{x}} \ \boxed{f(\mathbf{x})} \text{ a convex function}$$

$$s.t. \quad \boxed{h^{(i)}(\mathbf{x})} - \boxed{g^{(i)}(\mathbf{x})} \leq \mathbf{0}, \ i = 1, 2, \ldots, l$$

convex functions

Approximate optimization problem

$$\min_{\mathbf{x}} \ f(\mathbf{x})$$

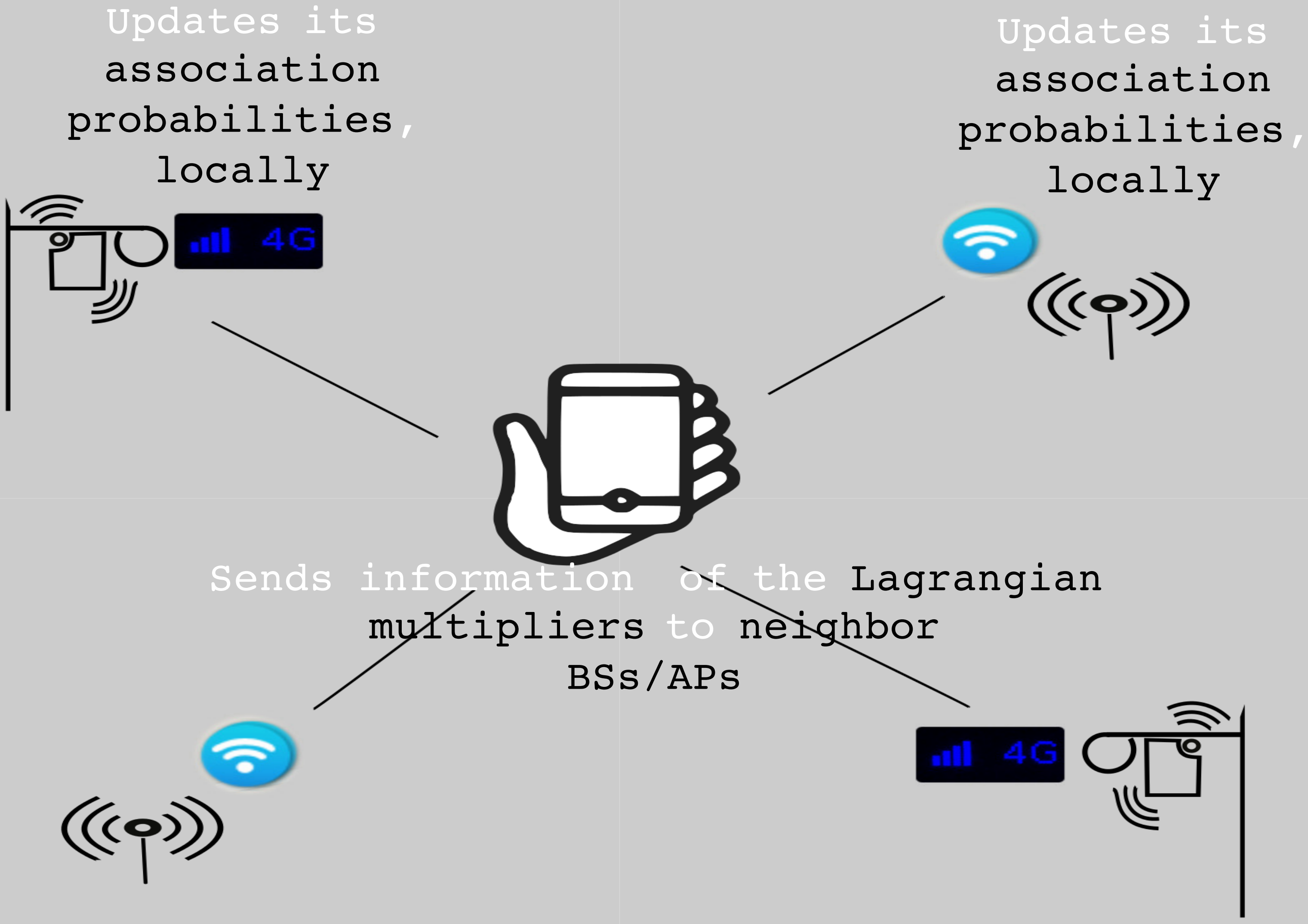
$$s.t. \quad h^{(i)}(\mathbf{x}) - \hat{g}^{(i)}(\mathbf{x}; \bar{\mathbf{x}}) \leq \mathbf{0}, \ i = 1, 2, \ldots, l$$

Trick: we form a maximal convex subset

$$-\hat{g}^{(i)}(\mathbf{x}; \bar{\mathbf{x}}) = -g^{(i)}(\bar{\mathbf{x}}) - \partial g^{(i)}_{\mathbf{x}}(\bar{\mathbf{x}})(\mathbf{x} - \bar{\mathbf{x}})$$

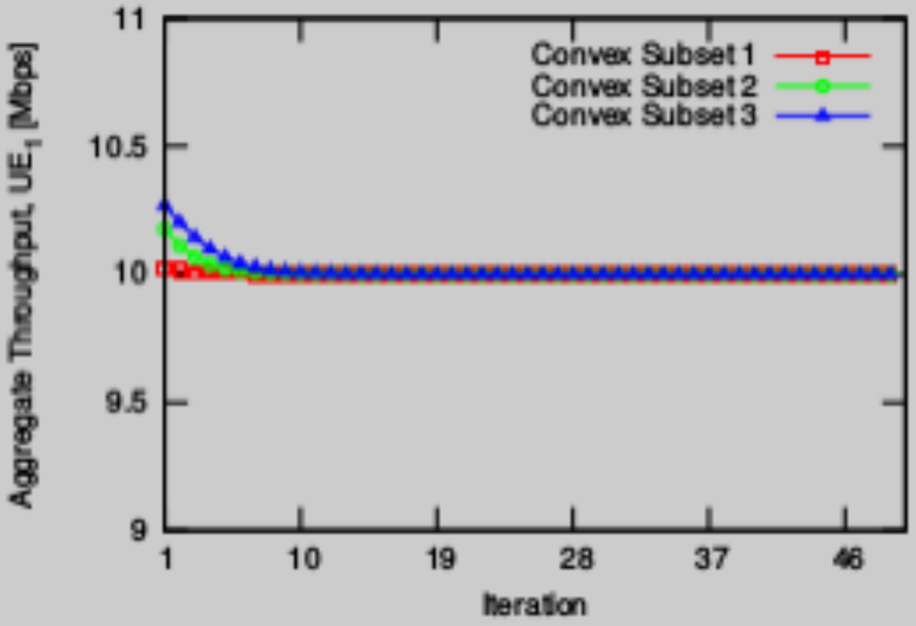
Algorithm and Information Exchange

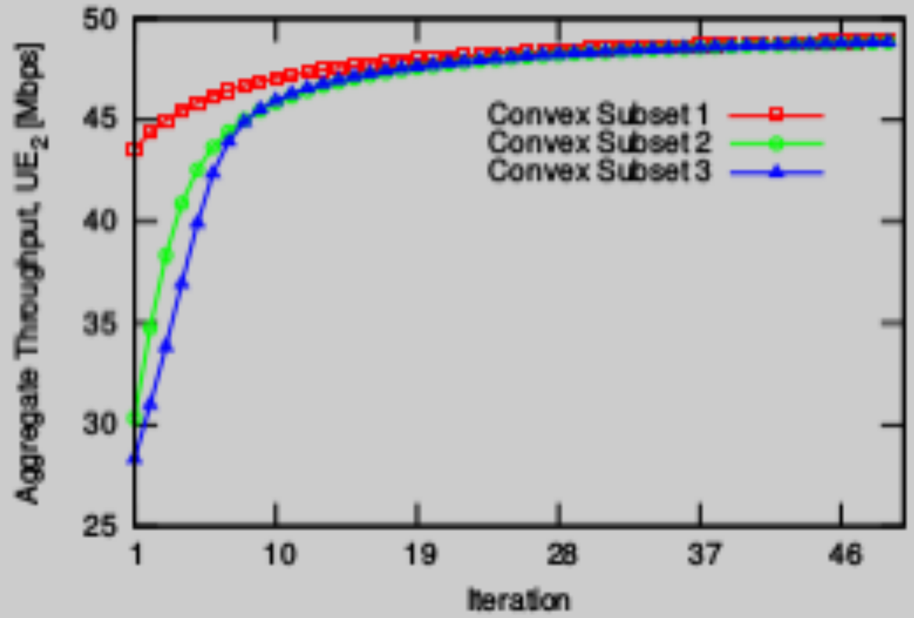
sol

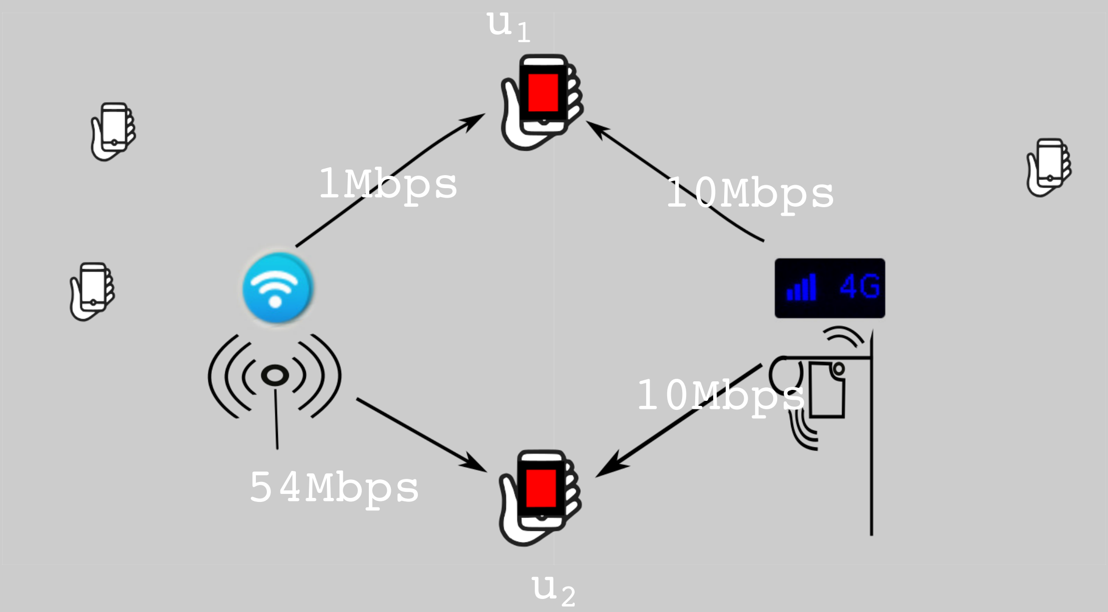


information

Some Numerical Results (convergence)

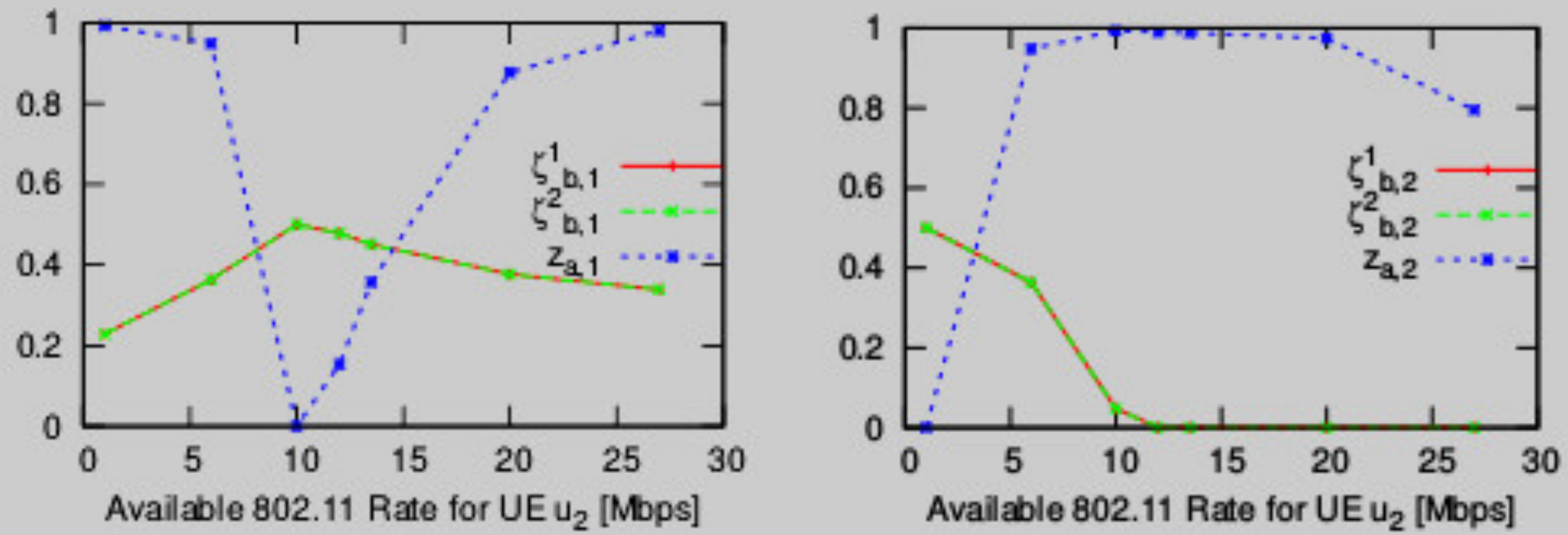






Some Numerical Results

Wi-Fi offload Example (more results can be found in [4,5])



[4] B. Partov, D. J. Leith , "Utility Fair Rate Allocation in LTE/802.11 Networks". Under minor revisions, IEEE Trans/ACM on Networking, June 2015

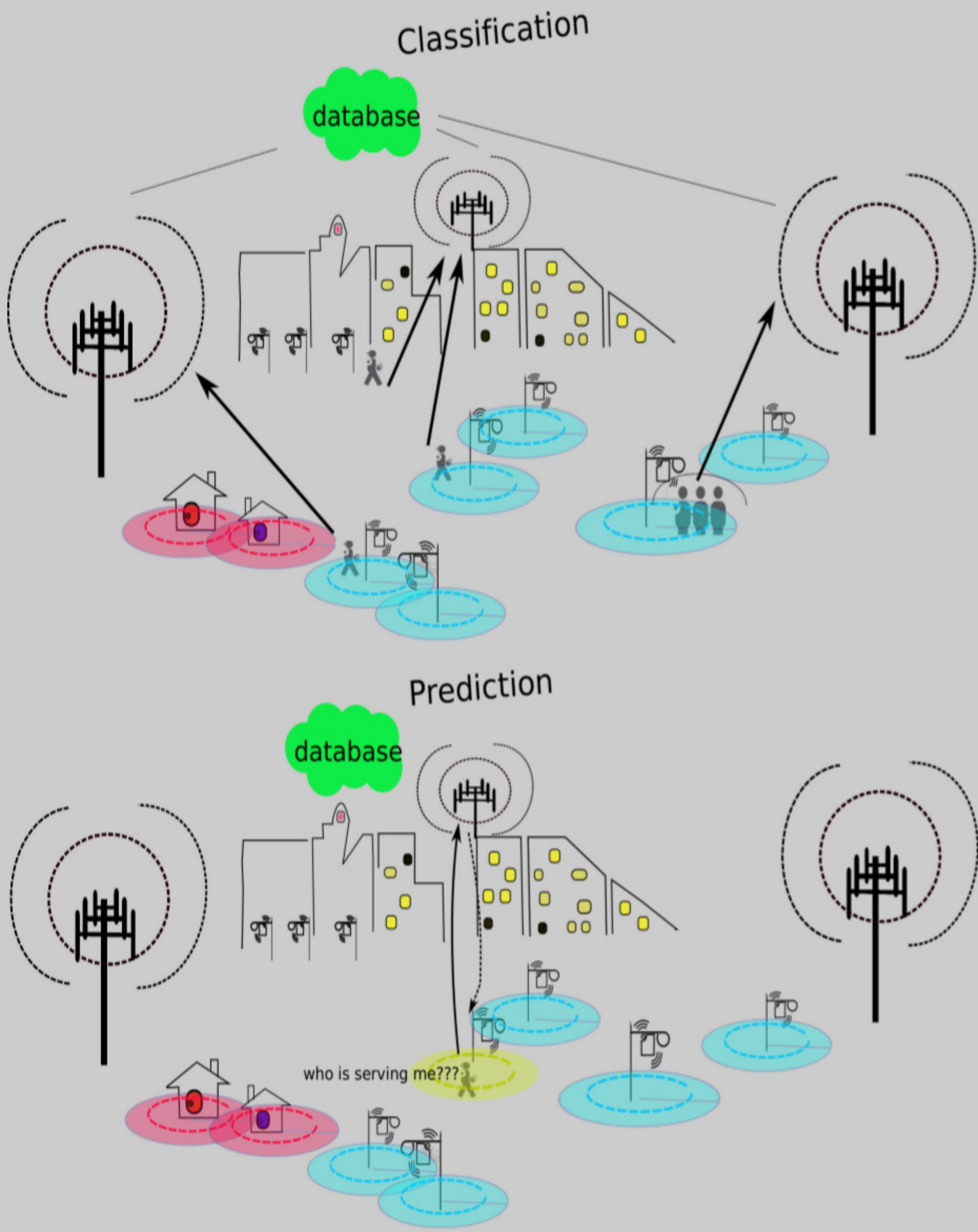
[5] B. Partov , D.J. Leith, “Utility Fair RAT Selection in multi-homed LTE/802.11 Networks”, Allerton, Sep 2015

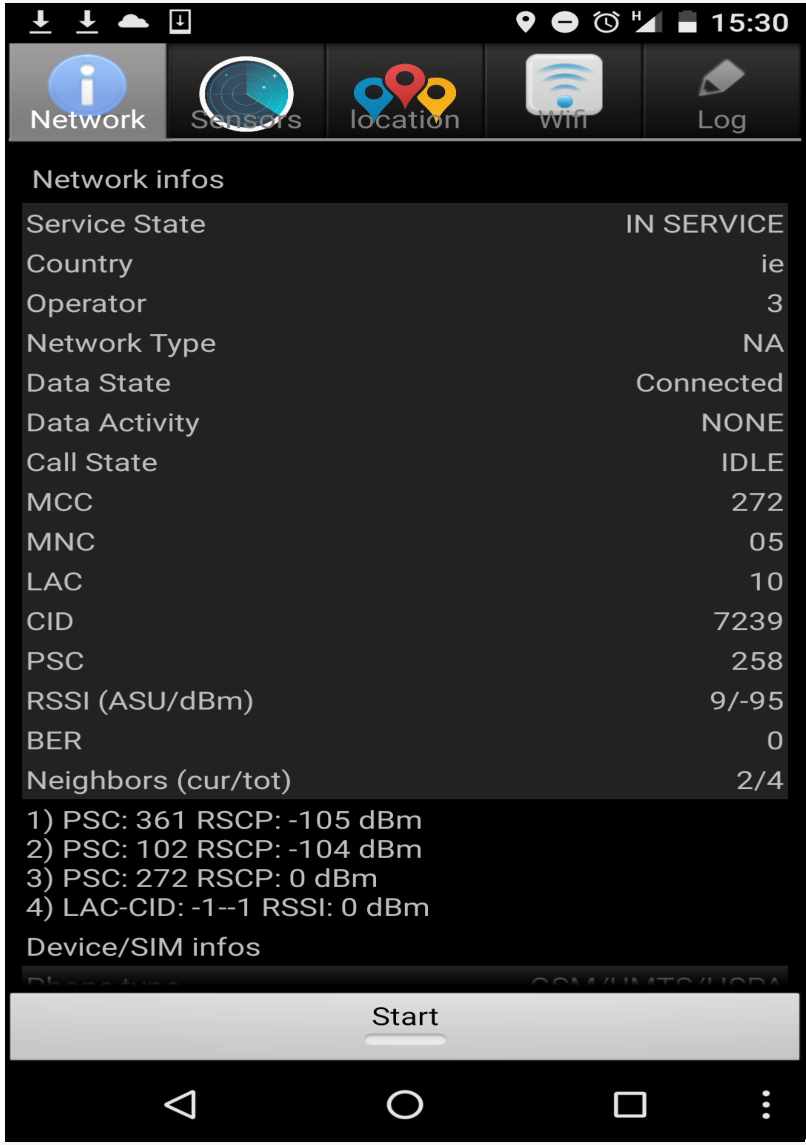
A power scheduling problem

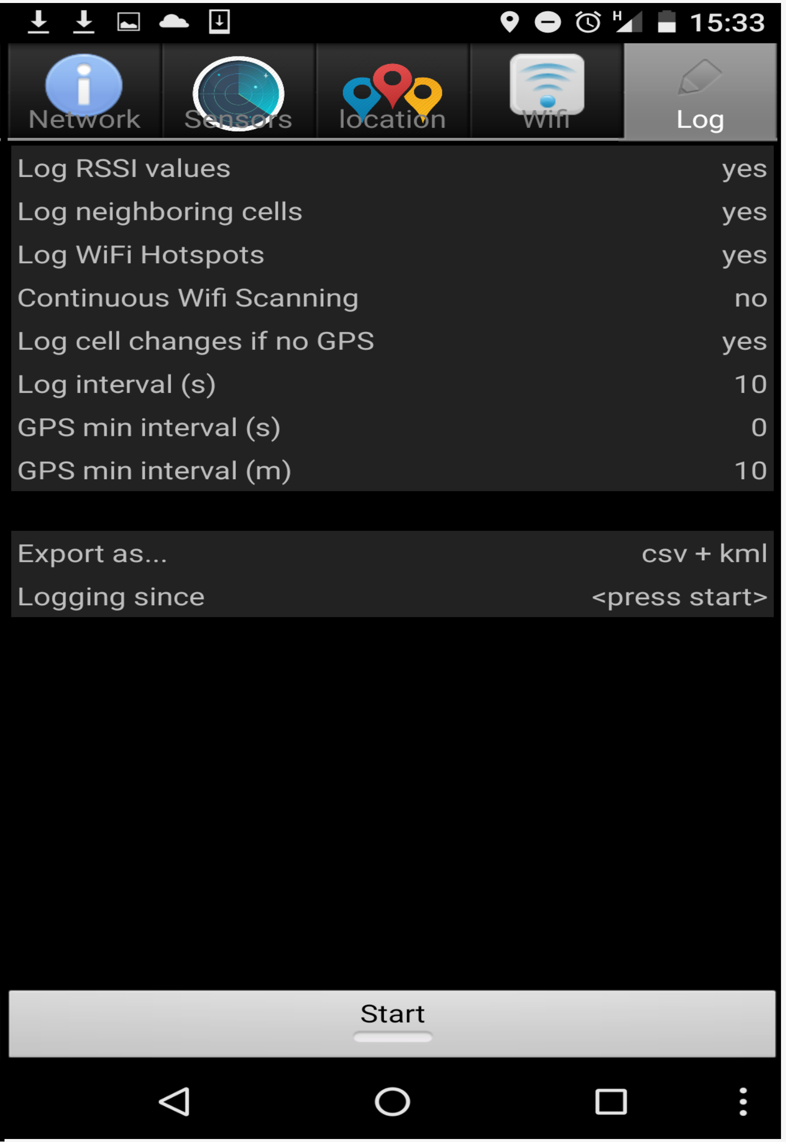
Small cells are densely deployed in the network

Users activity fluctuates spatially and temporally

How to predict users position in respect with the cells, so to minimize power Consumption and interference

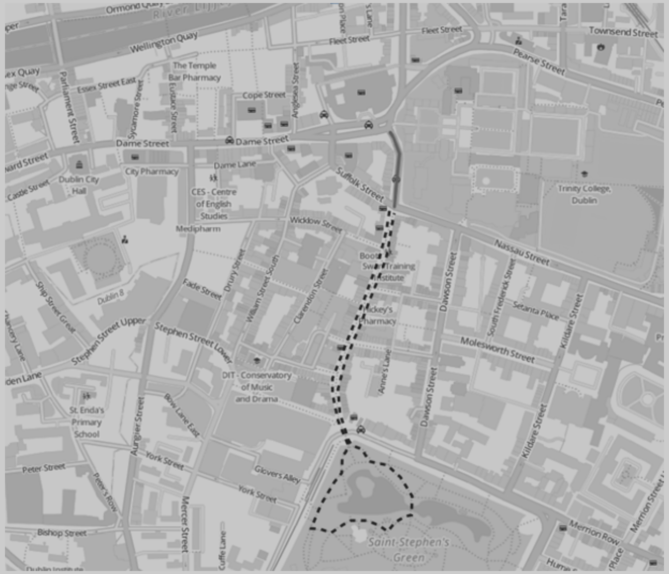






I logged user data reports in Dublin city center using a simple Android App

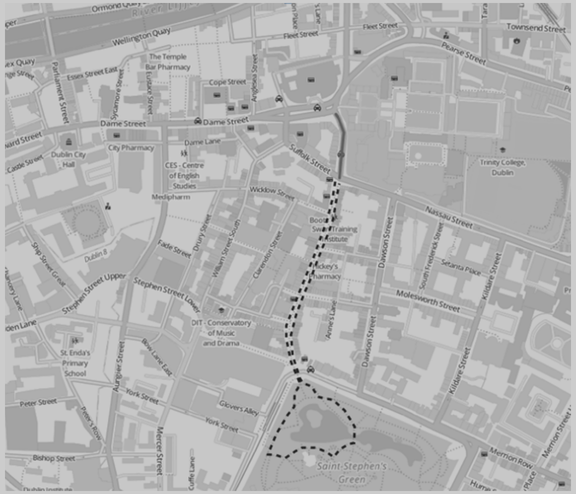
A Dataset of RF Fingerprints

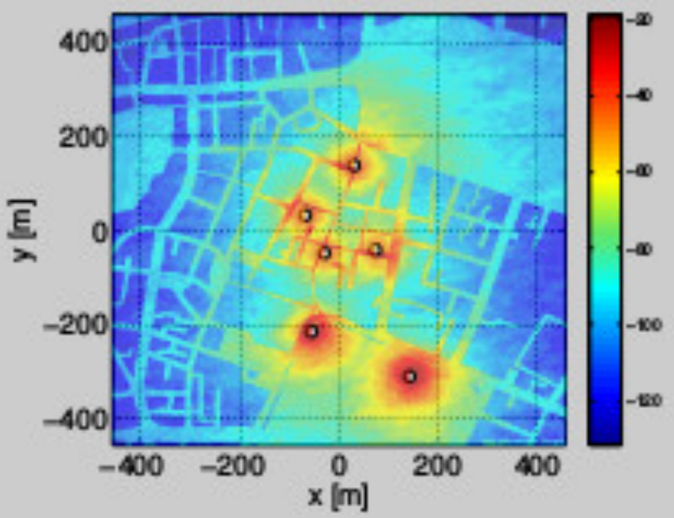


Sub-samples of RF fingerprint pilot powers in dBm where each dimension is marked by a distinct Primary Scrambling Code, PSC and each distinct measurement point is identified by a geographical coordinates in the form of (latitude, longitude).

Location\PSCs	212	204	252	300	120	45	236	292
(53.3400988,-6.2607508)	-	-69	-53	-	-105	-91	-68	-65
(53.3401079,-6.2607396)	-	-	-	-	-	-	-	-63
(53.3401169,-6.2607290)	-	-	-	-	-	-	-	-63
(53.3401227,-6.2607128)	-	-	-51	-	-	-	-	-
(53.3401297,-6.2607026)	-	-	-51	-	-	-	-	-
(53.340137,-6.2606895)	-	-	-51	-	-	-	-60	-59

Predicting the Serving Cells





Two stage classifier

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(1) Find Jaccard similarity index for observation-query pairs:

Training set of RF fingerprints

while $i \leq |\mathcal{T}|$ **do**

Query vector of user u

$$JS(Y_u, X_i) = \frac{|Y_u \cap X_i|}{|Y_u \cup X_i|}$$

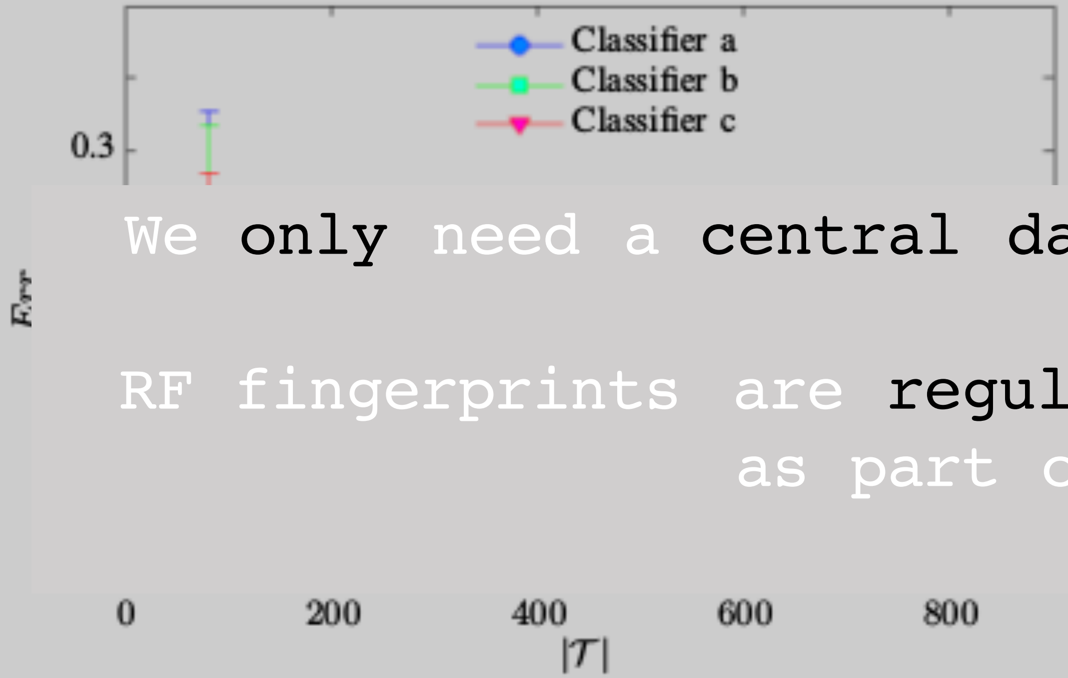
Observation i from the training set

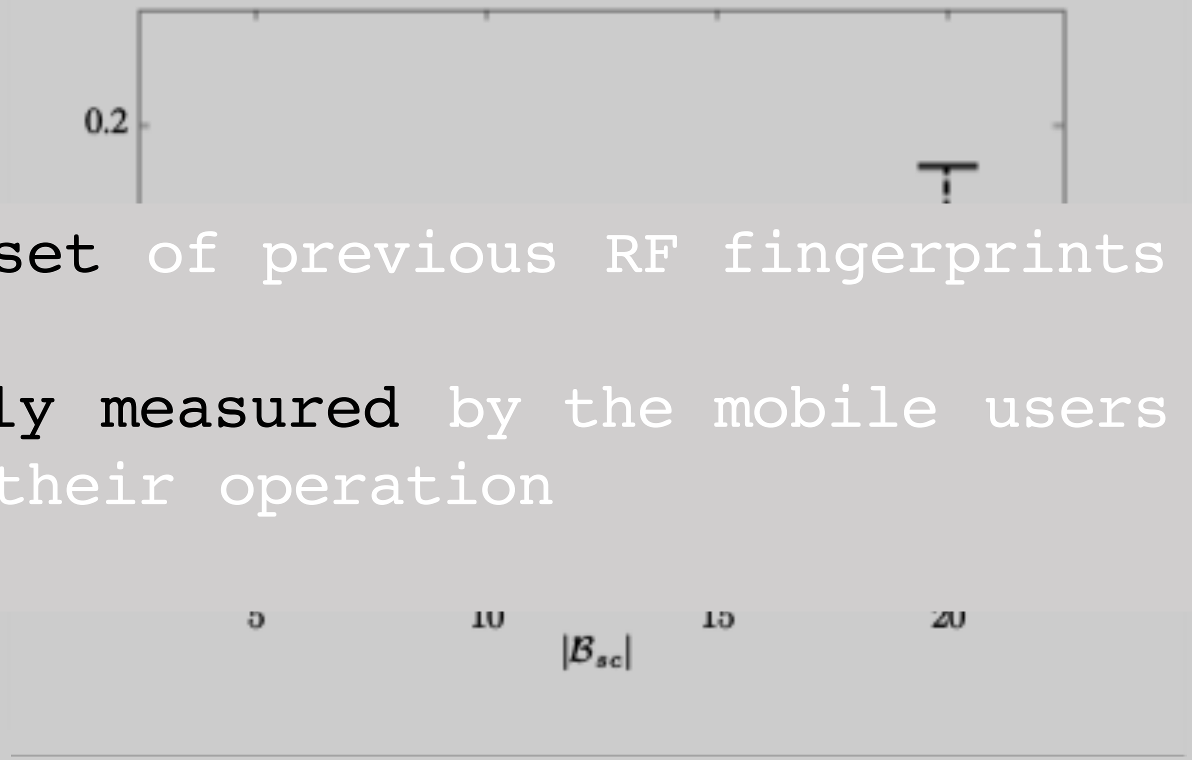
end while

Sort observations based on their Jaccard index

(2) Perform 1 norm K-Nearest Neighbour search on first n_{jac} **entries of** $JS(Y_u, \mathcal{T})$

Expected Prediction Error





We only need a central dataset of previous RF fingerprints

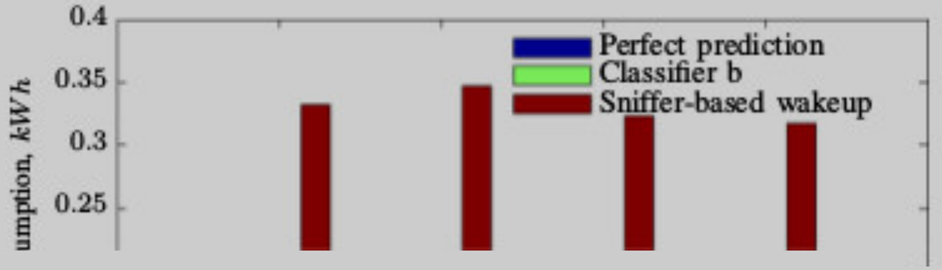
RF fingerprints are regularly measured by the mobile users as part of their operation

Expected prediction error, different classifiers

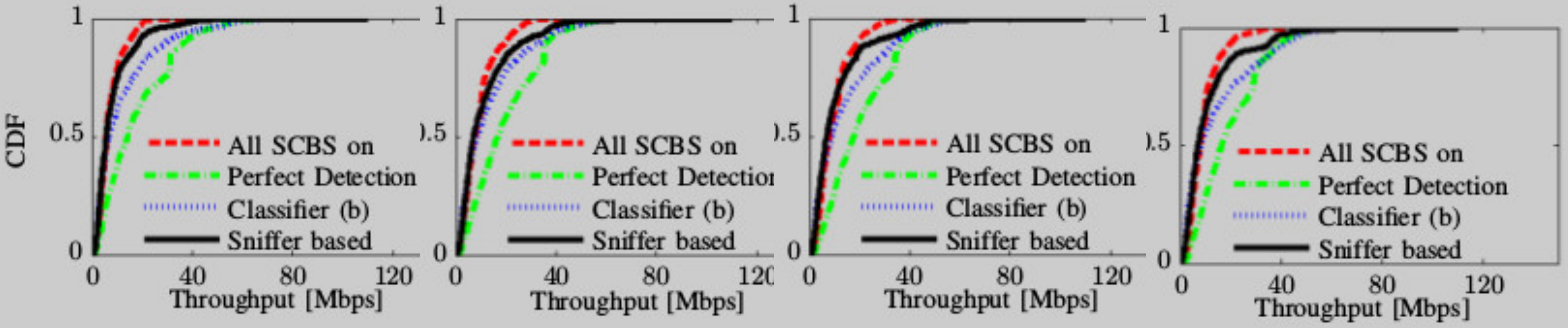
Expected prediction error, varying density of small cells

[3] B. Partov, et. al. , “Dynamic Idle Mode Control in Small Cell Networks”, IEEE ICC, June 2015

Some Results: Effects of Predictions on Power consumptions and user throughputs



Power consumption for different idle model schedulers



User throughputs for different idle model schedulers and different times of the day

Who Cares?

In addition to effectivity, operators like solutions that are simple i.e.:

1. They are scalable
2. They don't add significant signaling overhead
3. And have a fast convergence rate

All three applications presented in this talk are appealing in that they meet the above criteria while leading to improved network performance.

Future Directions

How to get user measurements?

Can we evaluate our solutions in real networks?

What about practical limitations that might not be visible to us?

Operator’s data?

are in aggregate form

Uncertainty in the data increases with increasing complexity of the network

under-representative (per operator)

Crowd sourcing?

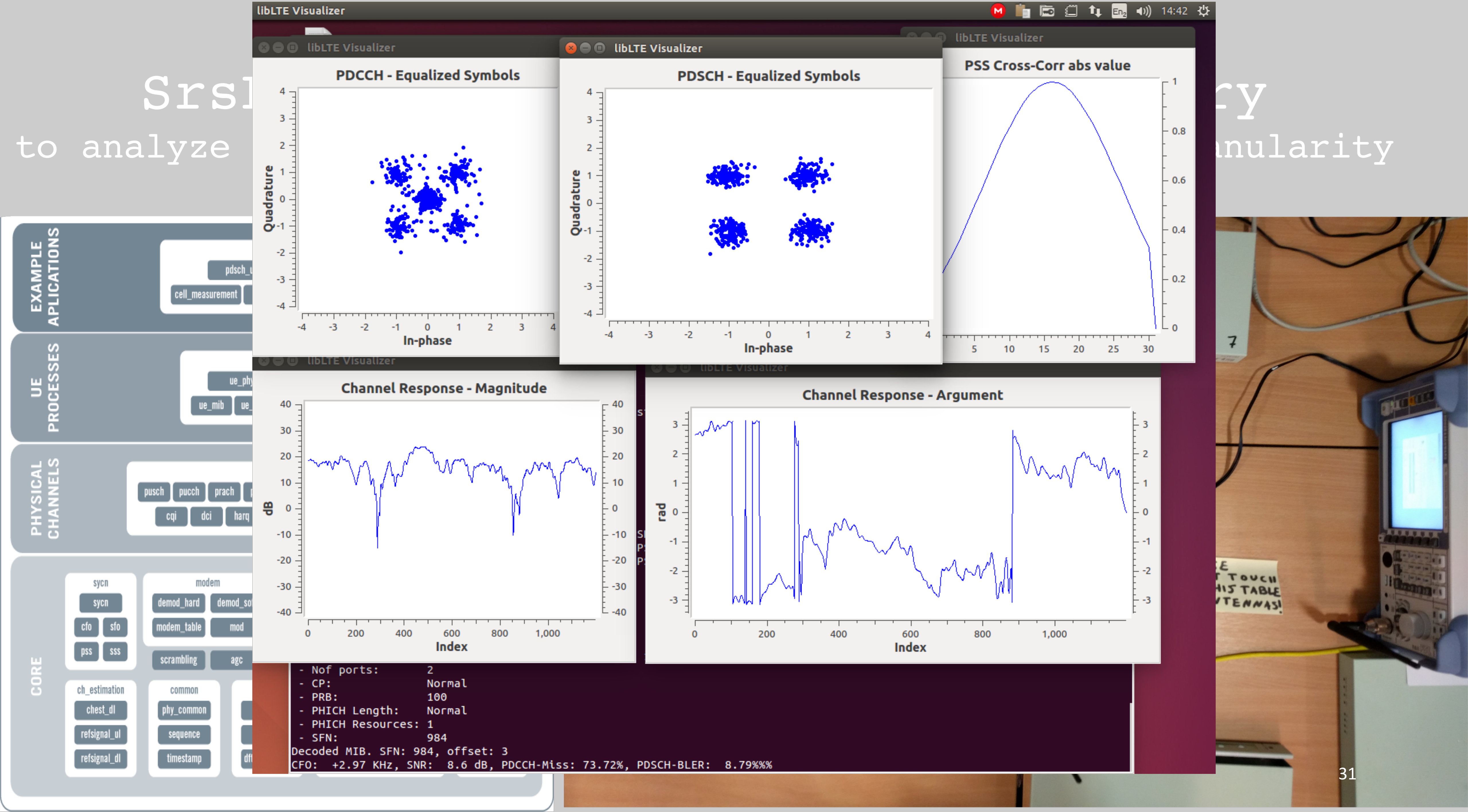
Under sampling problem

Application level data are course

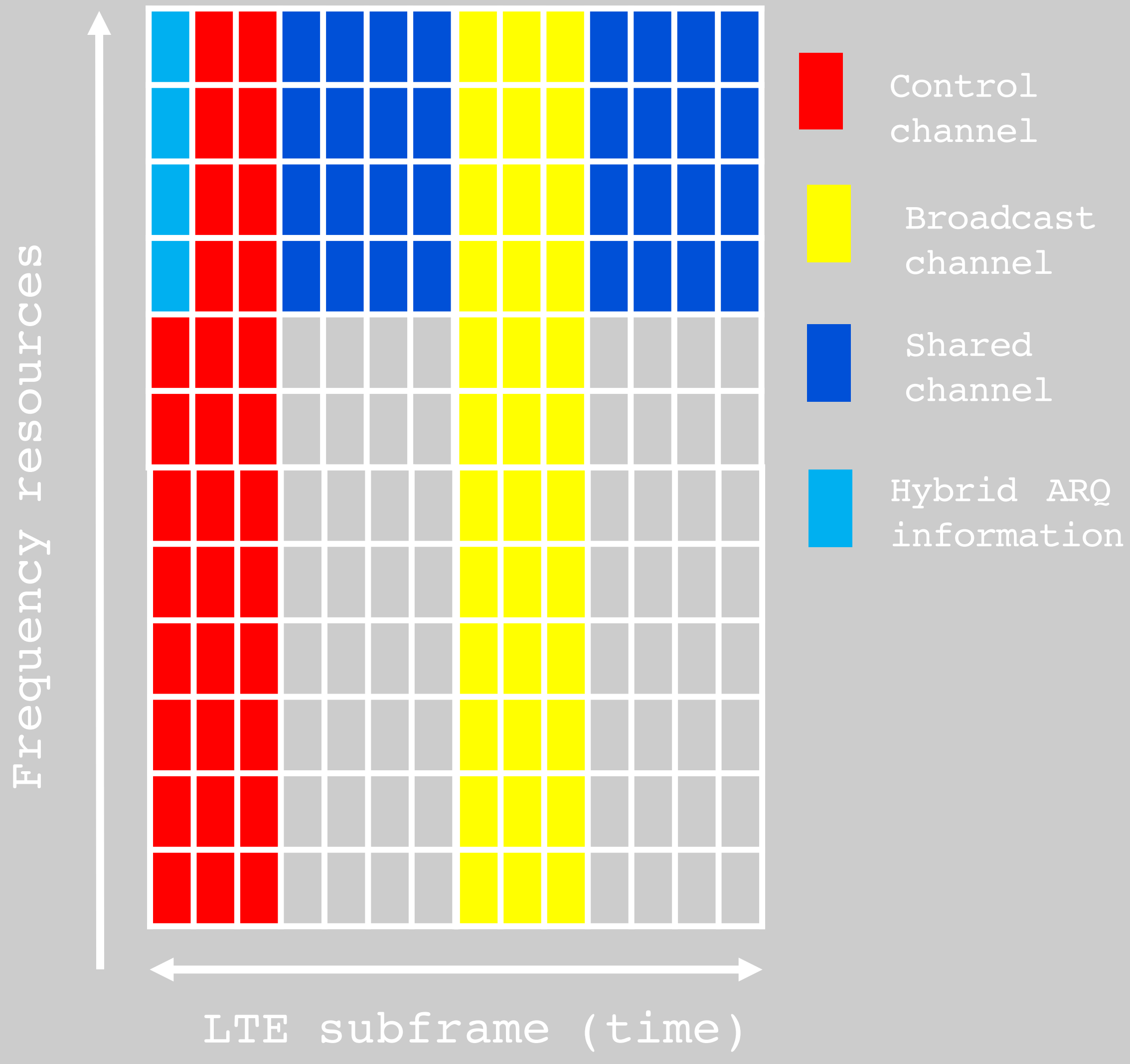
User privacy issues

Srsl... ry

to analyze ... anularity



Decoding the Control Channel Information



Valuable information may be extracted from control channels:

Number of active users connected to the cell

UL/DL Bitrate per user, UL/DL total bitrate in the cell

allocated PRBs in each sub frame and per user

Modulation and coding scheme per user

Number of UL/DL HARQ retransmissions per user and per cell

Approximate distance from sensor device and from user to base station

Average session duration per user and Sniffing of Paging messages

Potential Applications

Can be used to characterize network performance under various conditions
and to Monitor unusual behaviors in the network

To evaluate coexistence issues in the un-licensed band

Further this data can be used to provide smart services to the citizens e.g. traffic flow management and public safety measurements

Thank you

Appendix:
Detailed Expressions
And
More Results

Data rate as a function of tilt angles

$$\tilde{G}_{b,u}(\theta_b) = \tilde{G}_0 \tilde{G}_v(\theta_b, d_{b,u})$$

where $\tilde{G}_0$ is the maximum gain of the antenna,

$$\tilde{G}_v(\theta_b, d_{b,u}) = 10^{-1.2\left(\frac{\theta_{b,u}-\theta_b}{\theta_{3dB}}\right)^2}$$

$$\hat{G}_v(\theta_b, d_{b,u}) = \frac{-1.2\log 10}{\theta_{3dB}^2}\Big((\theta_{b,u} - \theta_0)^2 + 2(\theta_{b,u} - \theta_0)\theta_b\Big)$$

Data rate as a function of tilt angles

$$R_u(\Theta) = \min\{\bar{r}, r_u(\Theta)\}, \quad u \in \mathcal{U}$$

$$r_u(\Theta) = \frac{\beta_1 \omega}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \log(1 + \gamma_u^i(\Theta)/\beta_2)$$

$$\gamma_u^i(\Theta) = \frac{P_{R,u}(\theta_{b(u)})}{\sum_{c \in \mathcal{B} \setminus \{b(u)\}} \hat{P}_{R,u}(\theta_c) + \sigma_n^2}$$

where $P_{R,u}(\theta_b) := e^{G_{b,u}(\theta_b)} \ell_{b,u} p_b$ is the received power from base station $b(u)$ by user u, $\hat{P}_{R,u}(\theta_c) := e^{\hat{G}_{c,u}(\theta_c)} l_{c,u} p_c$ is the received power from base station $c \neq b(u)$ by user u and σ_n^2 noise power at the receiver.

Tilt angles problem: High-SINR Regime

$$\hat{R}_u(\Theta) = \min\{\bar{r}, \hat{r}_u(\Theta)\}, \quad u \in \mathcal{U}.$$

where

$$\hat{r}_u(\Theta) = \frac{\beta_1 \omega}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \log(\gamma_u^i(\Theta)/\beta_2)$$

$$L(\Theta, \Lambda) = -\sum_{u \in \mathcal{U}} U(\hat{R}_u(\Theta)) + \sum_{u \in \mathcal{U}} \lambda_u^1(\underline{r} - \hat{R}_u(\Theta)) + \sum_{b \in \mathcal{B}} \lambda_b^2(\underline{\theta} - \theta_b)$$
$$+ \sum_{b \in \mathcal{B}} \lambda_b^3(\theta_b - \bar{\theta})$$

Tilt angles problem: high SINR regime

Lemma 0.1 $h(x) = \log(\log(1 + e^x))$ *is concave and non-decreasing in* $x \in \mathcal{R}$.

Turning now to $R_u(\Theta)$, we begin by observing that

Lemma 0.2 $\log(r_u(\Theta))$ *is concave in* Θ.

We have

$$\log(r_u(\Theta)) = \frac{\beta_1 \omega}{|\mathcal{I}|} \sum_{i \in |\mathcal{I}|} \log(\log(1 + \gamma_u^i(\Theta)/\beta_2) = \frac{\beta_1 \omega}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \log(\log(1 + e^{\hat{r}_u^i(\Theta)}))$$

where $\hat{r}_u^i(\Theta) = \log(\gamma_u^i(\Theta)/\beta_2)$. That is, the mapping from vector Θ to $\log(r(\Theta))$ is the vector composition of $h(x)$ and $\hat{r}_u^i(\Theta)$. $\hat{r}_u^i(\Theta)$ is concave in Θ. By [p86]boyd2004convex, the vector composition of a non-decreasing concave function and a concave function is concave.

Users to BSs Association

LTE system model

$$\mathcal{R}_{lte} = \Big\{ \mathbf{r} : r_u = \sum_{b \in \mathcal{B}} \sum_{i \in \mathcal{I}} \zeta_{b,u}^i \beta_1 \omega^i \log\big(1 + \frac{\gamma_{b,u}^i}{\beta_2}\big), \underline{r} \le r_u \le \bar{r},\ 0 \le \zeta_{b,u}^i \le 1, \sum_{u \in \mathcal{U}} \sum_{b \in \mathcal{B}} \zeta_{b,u}^i \le 1,\ \forall i \in \mathcal{I} \Big\}$$

or

$$\mathcal{R}_{lte} = \Big\{ \mathbf{r} : r_u = \sum_{b \in \mathcal{B}} \sum_{i \in \mathcal{I}} \zeta_{b,u}^i \beta_1 \omega^i \log\big(1 + \frac{\gamma_{b,u}^i}{\beta_2}\big), \underline{r} \le r_u \le \bar{r},\ 0 \le \zeta_{b,u}^i \le 1, \sum_{(u,b) \in \mathcal{E}^i} \zeta_{b,u}^i \le 1,\ \forall i \in \mathcal{I} \Big\}$$

Users to BSs Association

Wi-Fi system model

The throughput of user u in WLAN a is given by

$$s_{a,u} = \lim_{k\to\infty} \frac{\sum_{t=1}^{k} \sum_{i\in\mathcal{M}_{a,t}} \mathcal{Y}_{i,u} L_{a,u}}{kT} = \lim_{k\to\infty} \frac{1}{k} \sum_{t\in\{s\in\{1,2,\ldots,k\}:\mathbf{A}_{u,s}=a\}} \sum_{i\in\mathcal{M}_{a,t}} \mathcal{Y}_{i,u} \frac{L_{a,u}}{T}$$

$$= \lim_{k\to\infty} \sum_{n=1}^{|\mathcal{U}_a|} \frac{|\mathcal{T}_{a,n}^{k}|}{k} \frac{1}{|\mathcal{T}_{a,n}^{k}|} \sum_{t\in\mathcal{T}_{a,n}^{k}} \sum_{i\in\mathcal{M}_{a,t}} \mathcal{Y}_{i,u} \frac{L_{a,u}}{T}$$

where $\mathcal{T}_{a,n}^{k} := \{s \in \{1, 2, \ldots, k\} : A_{u,s} = a, \mathbf{N}_{a,s} = n\}$ and we have used the fact that $\mathbf{x}_{i,u} = 0$ when $u \notin \mathcal{U}_a$.

$$s_{a,u} = z_{a,u} \sum_{n=1}^{|\mathcal{U}_a|} \frac{p_{a,u,n}\tau(1-\tau)^{n-1} L_{a,u}}{P_{idle,n}\sigma + P_{succ,n}T_{succ,a} + P_{coll,n}T_{coll}}$$

Users to BSs Association

Expansion of the standard form

$$f(\mathbf{x}) = -\sum_{u\in\mathcal{U}} \log(s_u + r_u)$$

$$h_u^{(1)}(\mathbf{x}) = s_u, \quad g_u^{(1)}(\mathbf{x}) = \sum_{a\in\mathcal{A}_u} e^{\tilde{\rho}_{a,u}} c_{a,u}$$

$$h_{a,u}^{(2)}(\mathbf{x}) = \tilde{\rho}_{a,u} - \tilde{w}_{a,u} + \sum_{v\in\mathcal{U}_a} \log(1 + e^{\tilde{w}_{a,v}}) - \log\left(\sum_{n=1}^{|\mathcal{U}_a|} \frac{T_{succ_a}}{T_{coll}} \frac{\psi}{\Psi_n} q_{a,u,n}\right),$$

$$g_{a,u}^{(2)}(\mathbf{x}) = 0$$

$$h_{a,u,n}^{(3)}(\mathbf{x}) = q_{a,u,n}, \quad g_{a,u,n}^{(3)}(\mathbf{x}) = \sum_{\substack{\tilde{\mathcal{U}}_a \in \\ \mathcal{P}_{n-1}(\mathcal{U}_a \setminus \{u\})}} \prod_{v\in\tilde{\mathcal{U}}_a} e^{\tilde{w}_{a,v}}$$

$$h_u^{(4)}(\mathbf{x}) = \sum_{a\in\mathcal{A}_u} e^{\tilde{w}_{a,u}}, \quad g_u^{(4)}(\mathbf{x}) = \sum_{a\in A_u} \frac{e^{2\tilde{w}_{a,u}}}{1 + e^{\tilde{w}_{a,u}}}$$

$$h_i^{(5)}(\mathbf{x}) = \sum_{u\in\mathcal{U}} \sum_{b\in\mathcal{B}} \zeta_{b,u}^i - 1, \quad g_i^{(5)}(\mathbf{x}) = 0$$

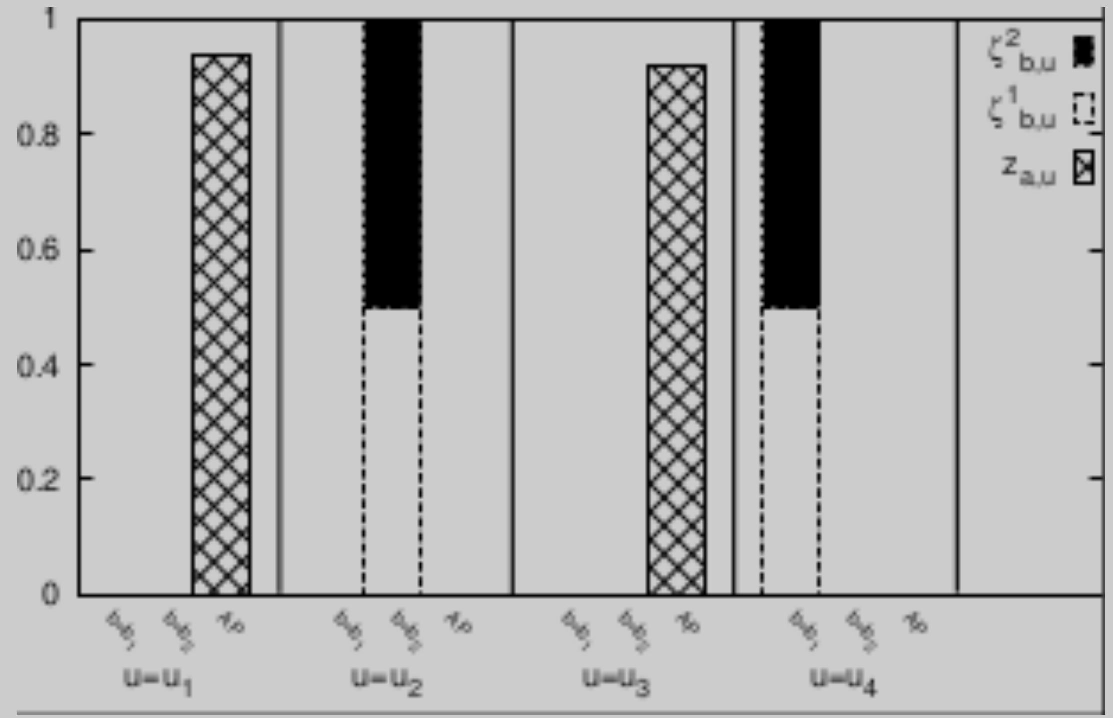
$$h_u^{(6)}(\mathbf{x}) = r_u - \sum_{b\in\mathcal{B}} \sum_{i\in\mathcal{I}} \zeta_{b,u}^i \beta_1 \omega^i \log\left(1 + \frac{\gamma_{b,u}^i}{\beta_2}\right), \quad g_u^{(6)}(\mathbf{x}) = 0$$

Users to BSs Association

LTE multi-homing

LTE multihoming example: data rates.

	PHY Rates [Mbps]			Technology Rates [Mbps]				
	BS b_1	BS b_2	AP	LTE b_1 only	LTE b_2 only	LTE (Maximum Rx Power)	802.11 only	Optimised Multi-RAT
u_1	26	25	54	6.5	6.25	8.27	7.51	15.36
u_2	10	25	27	2.5	6.25	2.4	3.75	12.5
u_3	5	29	54	1.25	7.25	3.56	7.51	14.8
u_4	11	10	13.5	2.75	2.5	2.29	1.88	5.5



Dynamic power scheduling in small cells: Classification

When all small cell base stations are active, a user is scheduled to a base station according to one of the following rules :

- Signal Strength: Maximum received pilot power:

$$b_u \in \arg\max_{b \in \mathcal{B}} p_b^p h_{b,u}$$

- Signal Quality: Maximum pilot SINR:

$$b_u \in \arg\max_{b \in \mathcal{B}} \gamma_{b,u}$$

where

$$\gamma_{b,u} = \frac{p_b^p h_{b,u}}{\sigma_n^2 + \sum_{k \in \mathcal{B} \setminus \{b\}} p_k h_{k,u}}$$

Dynamic power scheduling in small cells:
Calculation of the misclassification error

$\hat{\mathcal{F}}(X)$ and $\boldsymbol{b}$ denote the predicted and target cell association vectors respectively. A loss function is defined as a mismatch between the classifier's predictions and the target values:

$$\mathrm{P}(\boldsymbol{b}, \hat{\mathcal{F}}(X_u)) = \mathbb{1}_{(\boldsymbol{b} \neq \hat{\mathcal{F}}(X))}$$

The generalisation error is the prediction error over an independent test sample:

$$Err_{\mathcal{T}} = \mathbb{E}_X[\mathrm{P}(\boldsymbol{b}, \hat{\mathcal{F}}(X)) \mid \mathcal{T}]$$

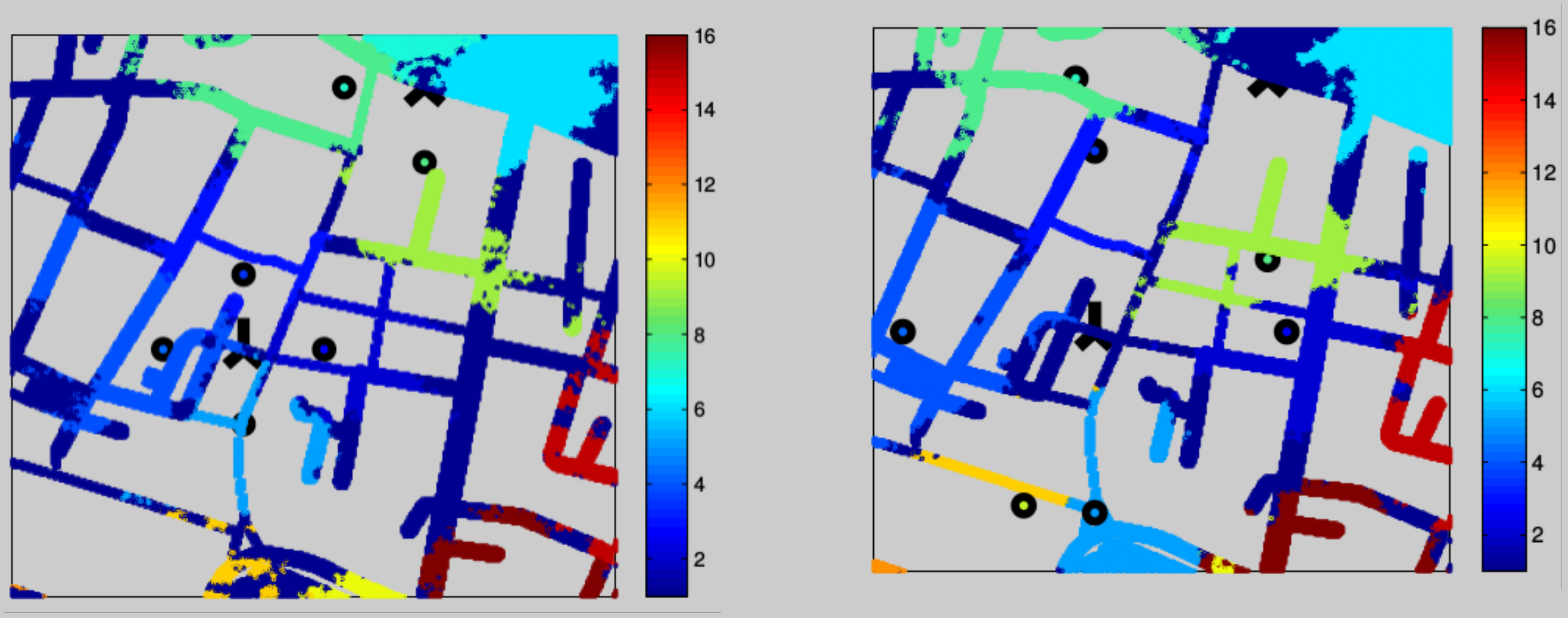
Expected prediction error, on the other hand averages over everything that is random including the randomness in the training set that produced $\hat{\mathcal{F}}$:

$$Err = \mathbb{E}[\mathrm{P}(\boldsymbol{b}, \hat{\mathcal{F}}(X))] = \mathbb{E}[Err_{\mathcal{T}}]$$

Here we referred to $Err_{\mathcal{T}}$ as the misclassification error of classifier trained on $\mathcal{T}$, and Err as the expected misclassification error.

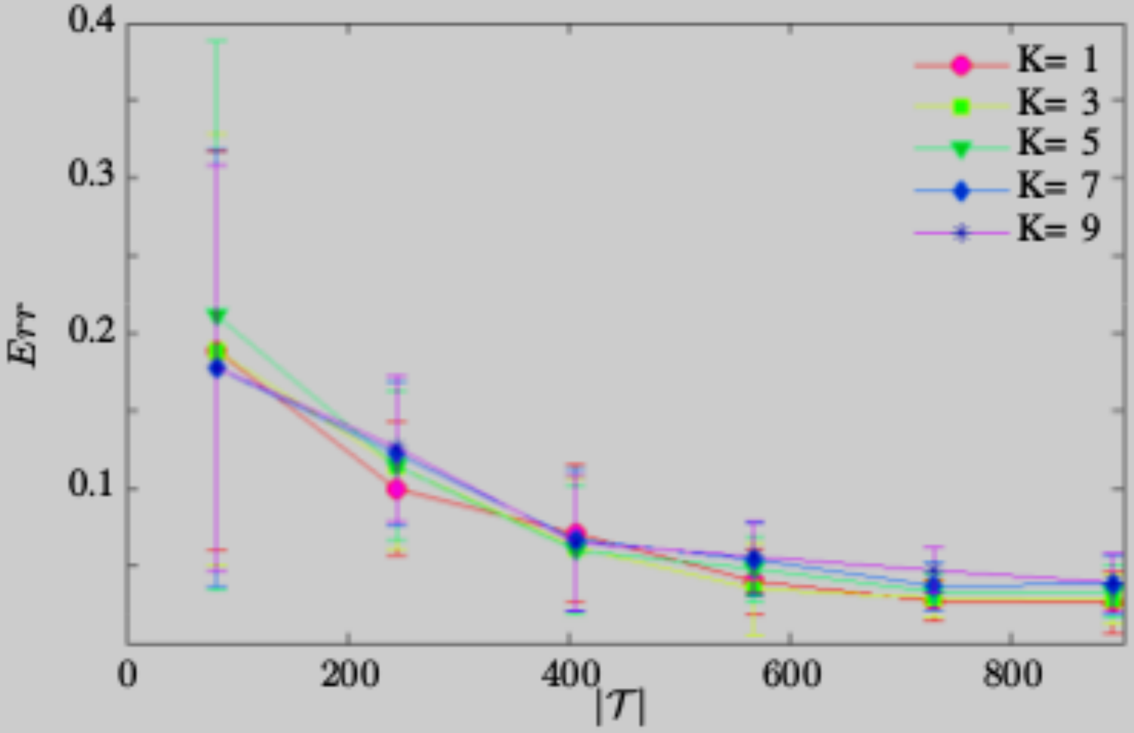
Dynamic power scheduling in small cells:

small cell deployments

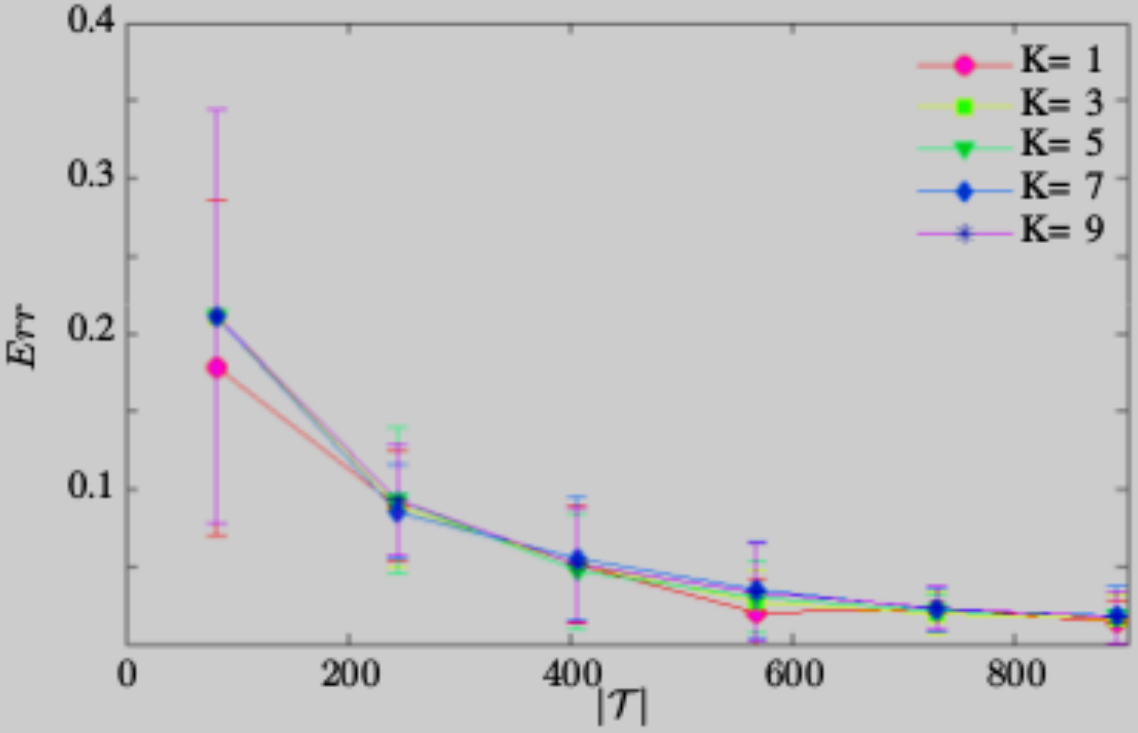


Dynamic power scheduling in small cells:

Varying number of KNN neighbors



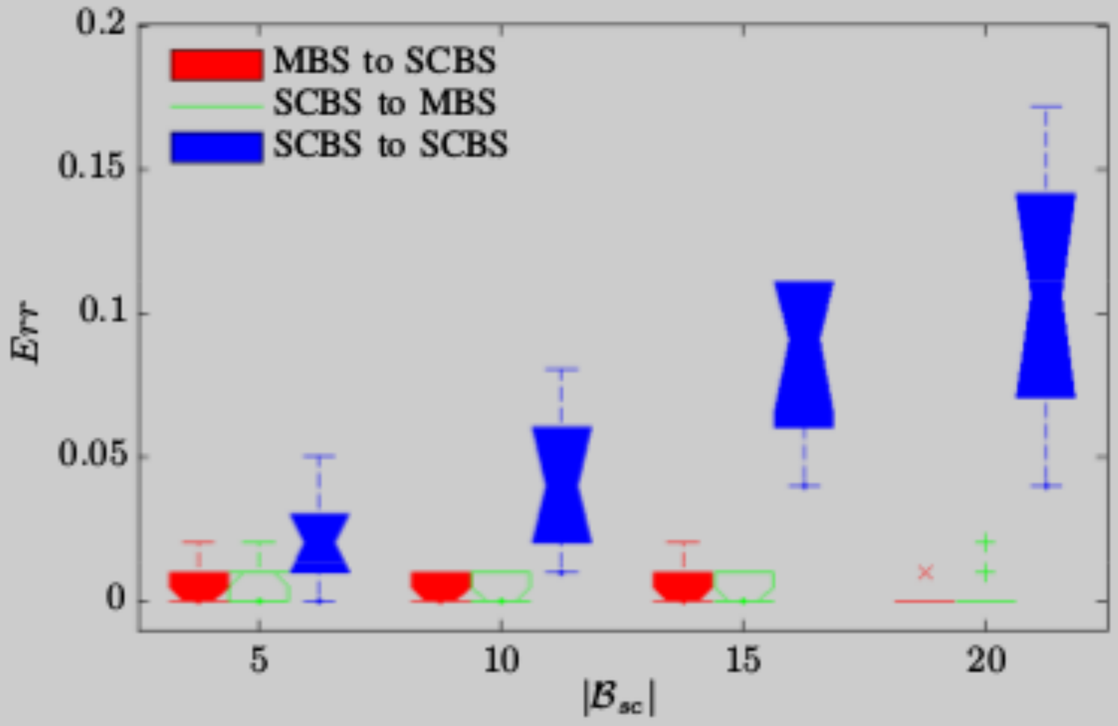
Classifier b



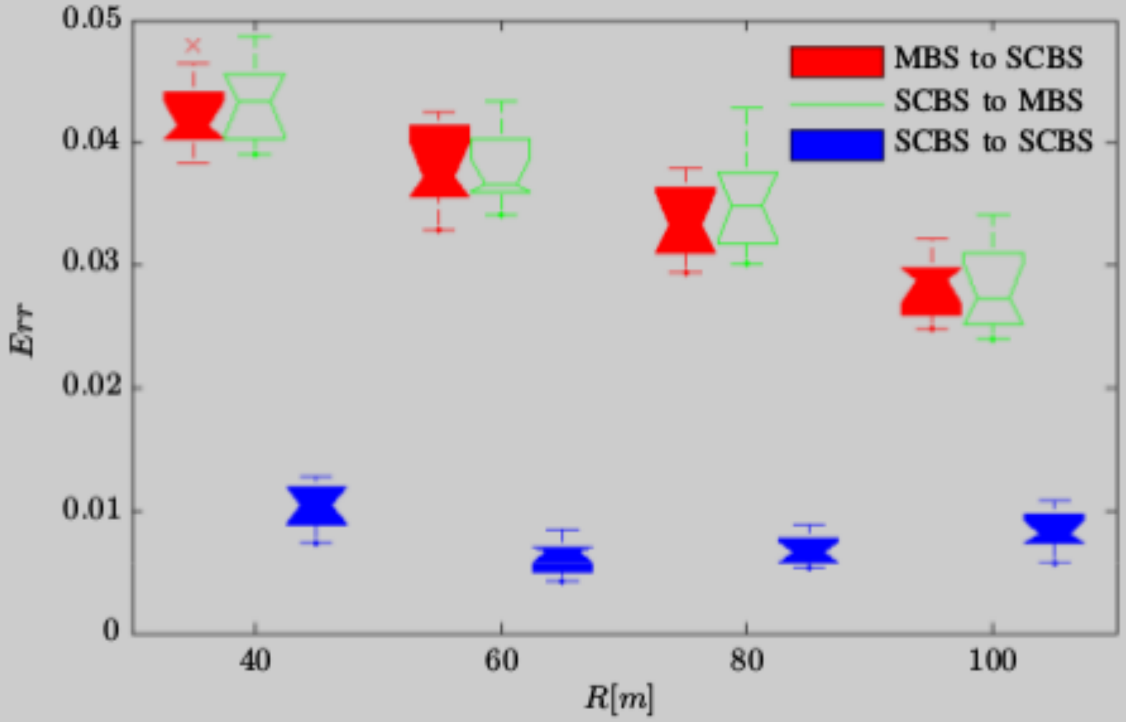
Classifier c

Dynamic power scheduling in small cells:

Misclassification error by type



Deployment scenario:
Equally spaced small cells



Deployment scenario:
Small cells deployed at cell edges