Towards Efficient and Robust Self-organizing Wireless Cellular Networks

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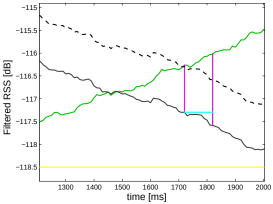
SON functionalities (use cases)

- Current approaches focus on isolated SON functionalities:
  - optimization and automation of handovers (HO)
  - load balancing (LB)
  - RACH optimization
  - capacity (interference coordination)
  - coverage hole detection and compensation
  - ...

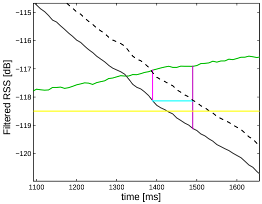
Outline

Handover optimization variables and objectives

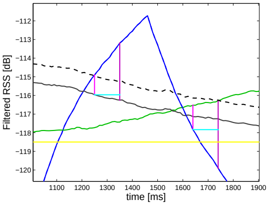
- Handover optimization variables (Handover parameters)
  - Global: HOM, TTT, filter coefficient K
  - Local: CIO
- Handover objectives:
  - Handover failure rate (HFR)
  - Handover rate (HR): overall HOs per unit time



“normal” HO



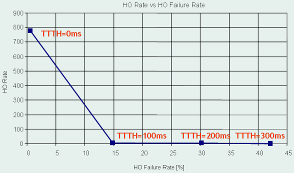
“too late” HO



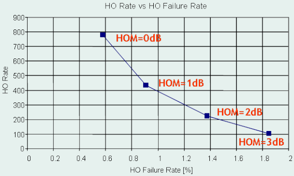
“too early” HO

Handover optimization challenges

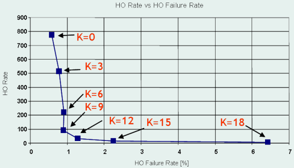
- Unknown and time-varying trade-off between HFR and HR
- Unknown and time-varying dependence on the HO parameters
- Global HO parameters for local problems



TTTH (HOM=0; K=0)



HOM (TTTH=0ms; K=0)



K (HOM=0; TTTH=0ms)

- Optimization based on partial information and some estimates

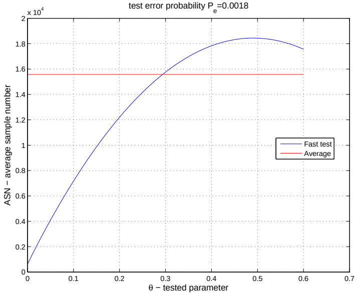
  $\Rightarrow$ Incompleteness and Uncertainity

Approach to handover optimization

- Minimize HR subject to HFR $\leq$ THRESHOLD (very small)
- Detect handover problems fast and reliably

$$\text{HANDOVER\_PROBLEM} = \begin{cases} \text{YES} & \text{HFR} > \text{THRESHOLD} \\ \text{NO} & \textit{otherwise} \end{cases}$$

- Handover problem detection is a hypothesis testing problem
  - No need for estimating HFR
  - Handover problem detection is performed faster if THRESHOLD is small



HO optimization challenges

HO optimization algorithms must make use of partial information and incorporate uncertainties.

- Learning algorithms: Take samples of HR for different HO parameters and test the constraints.
  - Use partial information to restrict the sample set
  - Optimize the choice of the next sample so as to
    - maximize the information increase or
    - minimize the expected error or
    - minimize some costs or
    - ...
  - Estimate HR and HFR for each sample.
  - Choose the HO parameters with the best performance

Handover: estimation of HO rates

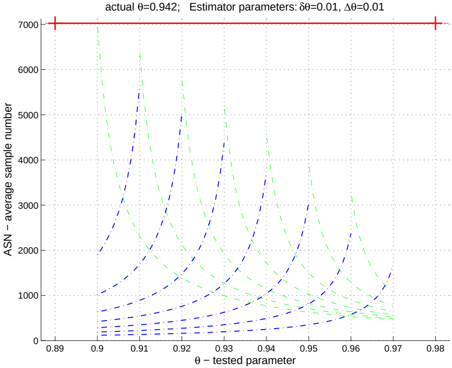
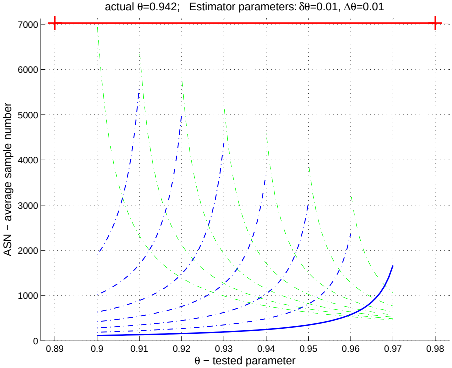


Figure: Rate estimator. The red line marks the actual confidance interval of the parameter θ (*e.g.*, a HO success rate).

Handover: estimation of HO rates



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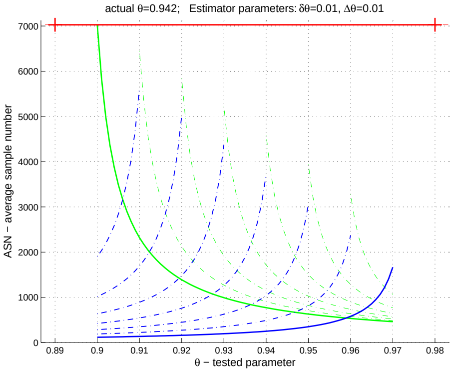

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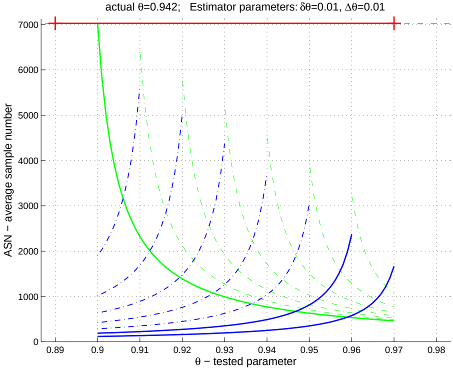

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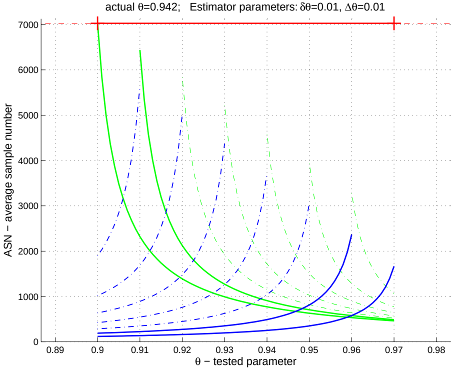

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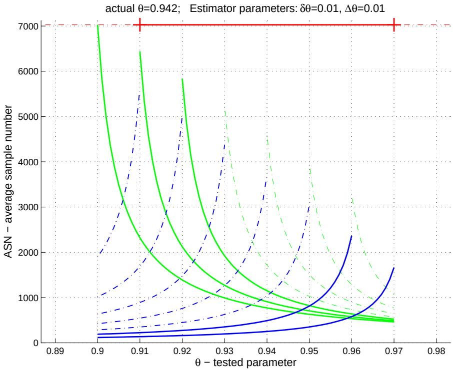

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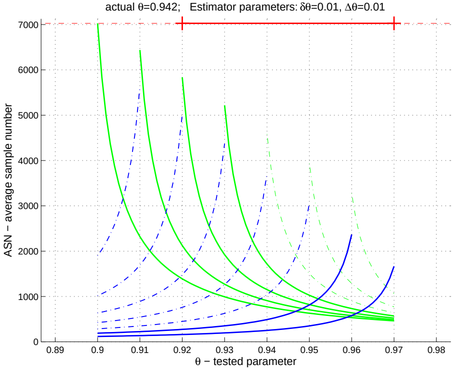

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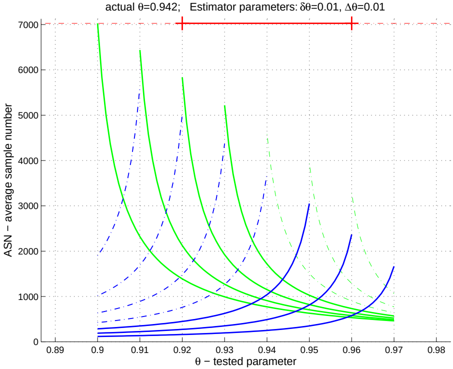

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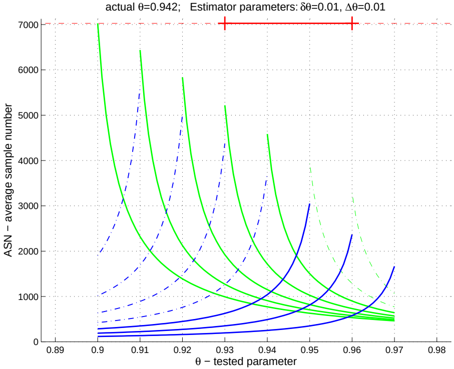

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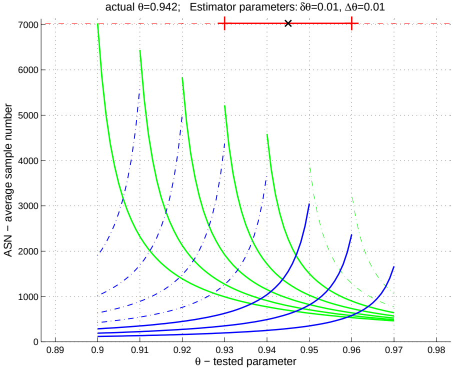

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Handover: Further extensions

- Stochastic optimization of global handover
  - Parametric or non-parametric Bayesian-like approaches (the objective function is a realization of a stochastic process)
  - Simulated annealing
  - Adaptive random search procedures
  - ...

Outline

1. Handover
2. Load Balancing
3. RACH Optimization
4. Use Cases Interaction

Load balancing (LB) objectives

- LB input parameters
  - CQI
  - Load indicator
- LB optimization variables
  - CIO (HO)
  - $Q_{offsets}$ (cell reselection)
- LB objectives
  - Uniform load distribution

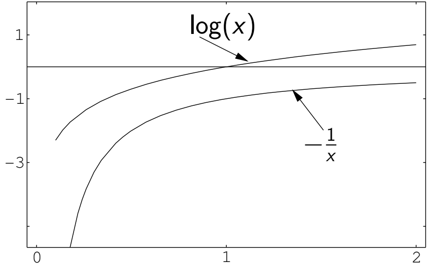
Approach to load balancing

Approximation of max-min fairness by aggregate utility maximization

$$\begin{array}{ll} \textbf{maximize} & \sum_{m=1}^{M} U(x_m) \\ \textbf{subject to} & \text{operational constraints} \end{array}$$

- Examples:

$$U(x) = \begin{cases} \frac{x^{1-\alpha}}{1-\alpha} & \alpha \geq 2 \\ \log x & \end{cases}$$



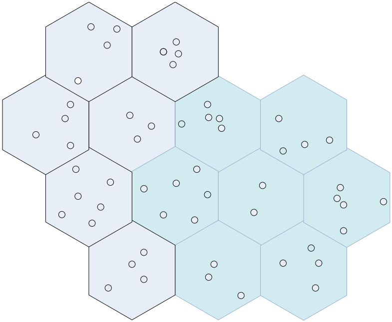
Load definition proposal

Load definition

$$x_m = \sum_{n=1}^{N} a_{n,m} \cdot \frac{\gamma_n}{w_{n,m}} \quad \begin{array}{l} \leftarrow \text{QoS requirement} \\ \leftarrow \text{bandwidth cost} \end{array}$$

where $a_{n,m} = 1$ if UE n is assigned to eNB m, otherwise $a_{n,m} = 0$.

- Reformulation of the problem as a convex optimization problem
- Decomposition of Lagrange dual function
  - optimal load distribution, optimal load association, minimal costs



- Exchange information among neighboring BSs:
  - Load price λ_m
  - Interference cost J_m
- Find:
  - Master BS ($\max \lambda$)
  - Slave BS ($\min(J + \alpha\lambda)$)
- UE selection
- HO decision (CIO)

LB algorithm Proposal

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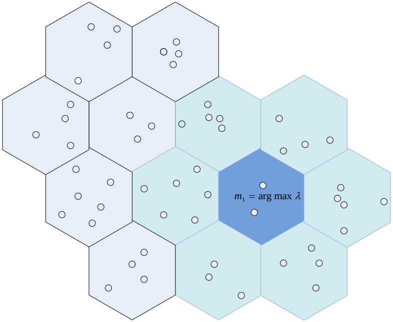

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  steepest decent

  increase aggregate utility
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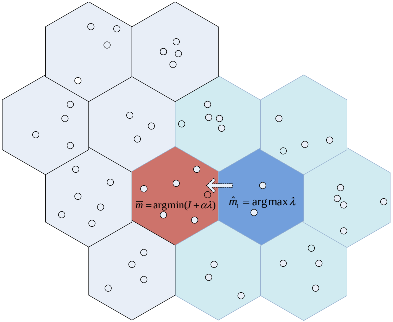

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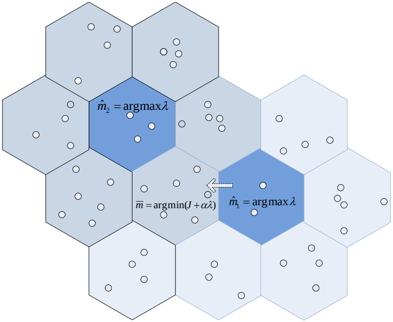

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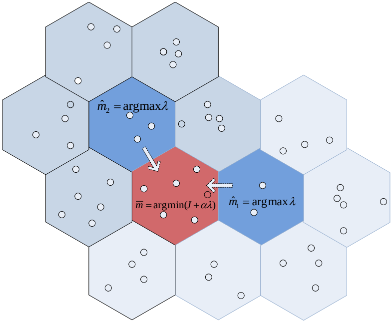

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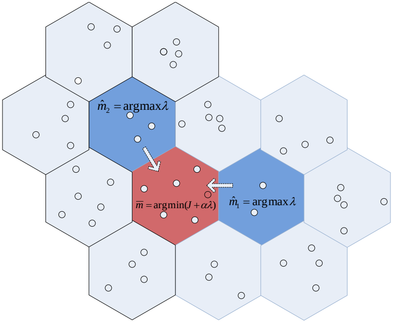

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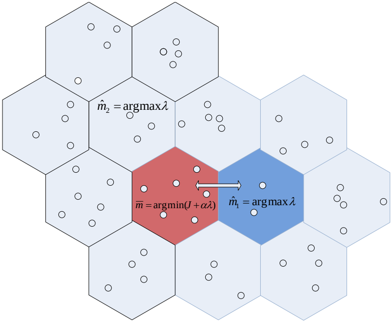

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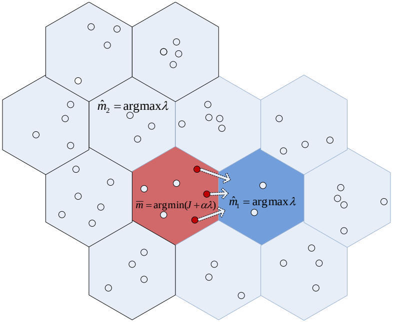

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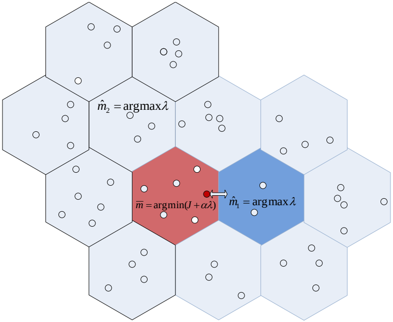

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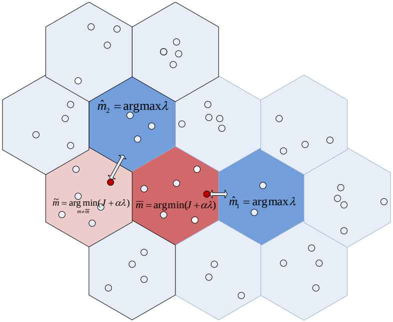

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Outline

RACH optimization variables and objectives

- RACH input parameters
  - UE report: Attempts m
  - Performance data: CP, DMP
- RACH optimization variables
  - Backoff probability
  - Target received power
- RACH optimization objectives
  - Improve the Access Probability (AP)

$$AP = (1 - DMP)(1 - CP)$$

$$\Rightarrow \text{decrease } DMP,\ CP$$

Approach to RACH optimization

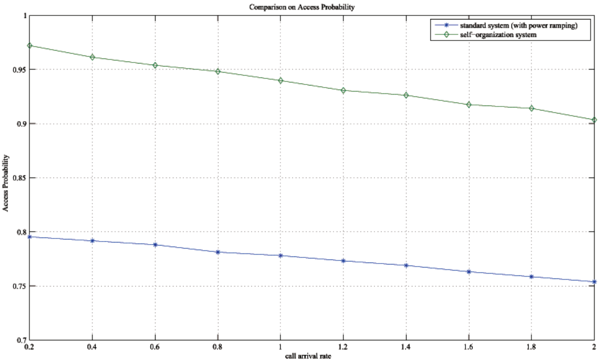
1. Backoff probability control for contention resolution
2. Self-tuning power control for detection improvement

- UE reports attempts it has needed to obtain access
- BS estimates the AP and the number of users in state m
- BS computes a contention level and broadcasts it to the UEs
  - The contention level is found by minimizing a Lyapunov drift
- Each UE computes its backoff probability

Simulation results

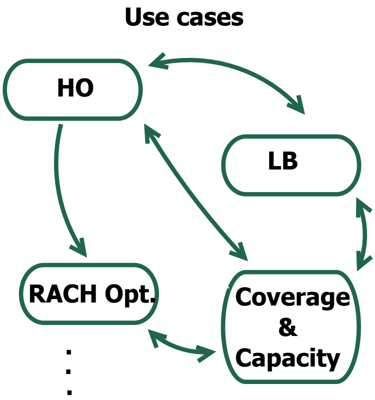
Scenario A: Fixed backoff probability, power ramping

Scenario B: Backoff probability control, open loop power control



Outline

Interaction among Use Cases



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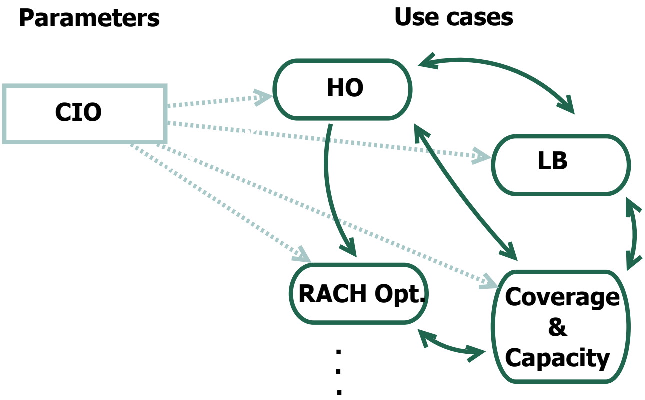

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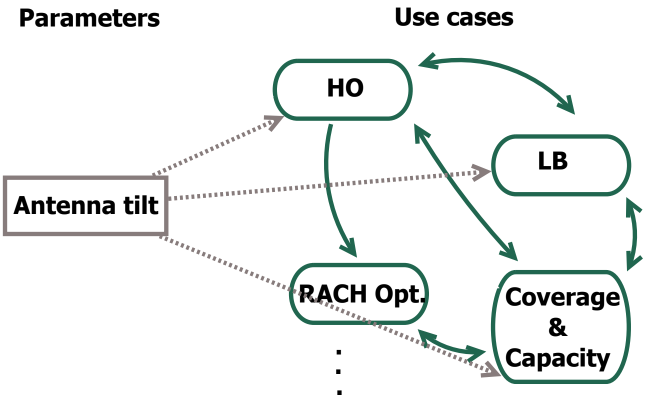

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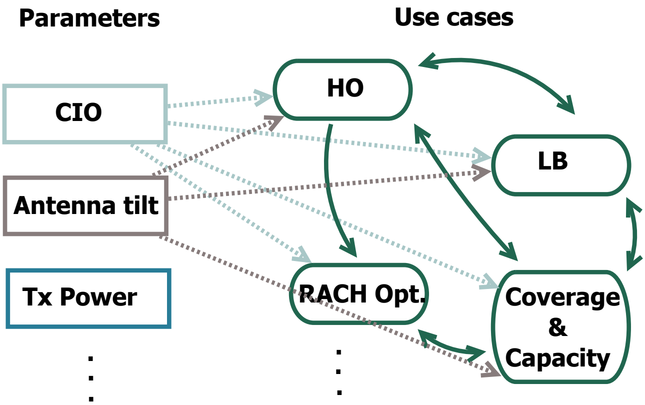
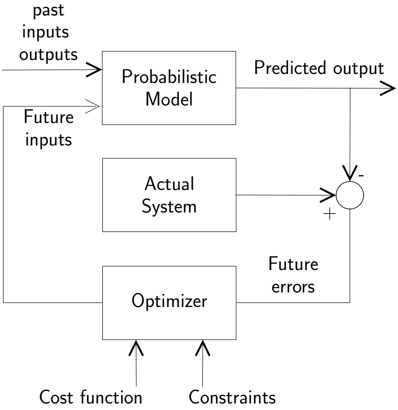


Model-based control for cross-use-case protocols



Cross-use-case SON protocols

- Define cost function and constraints
- Identify common (shared) input parameters
- Choose a (parametrized) model for the SON use cases
  - Model interdependencies between different SON use cases
  - Incorporate the constraints
  - Each use case is optimized separately on a shorter time scale
- Predict future network outputs given common input parameters (control input)
- Use measured network outputs and new parameter estimates to improve the model
  - Machine learning, Bayesian inference