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Optimizing Client Association in 60 GHz Wireless Access Networks

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CWC 22.05.13

Outline

- Past, Present and Future in wireless communications
- 60 GHz millimeterWave wireless technology
- Optimizing resource allocation
- Distributed client association (DAA)
- Numerical analysis of DAA
- Conclusions and open research topics

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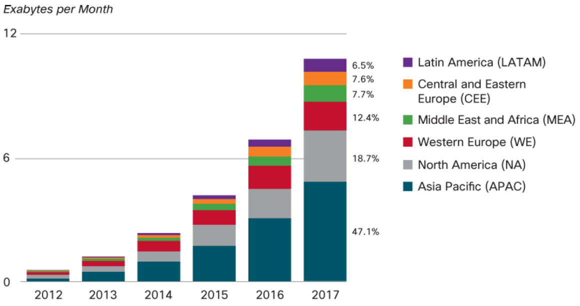
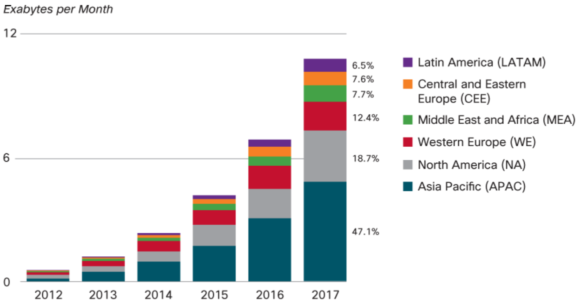
Growth of Mobile Traffic



Source: Cisco VNI Mobile Forecast, 2013

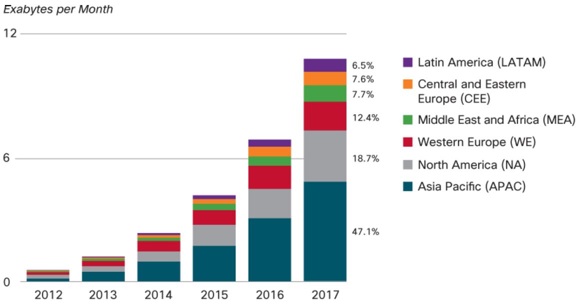
Growth of Mobile Traffic



Source: Cisco VNI Mobile Forecast, 2013

2012: 70% mobile traffic growth compared to 2011

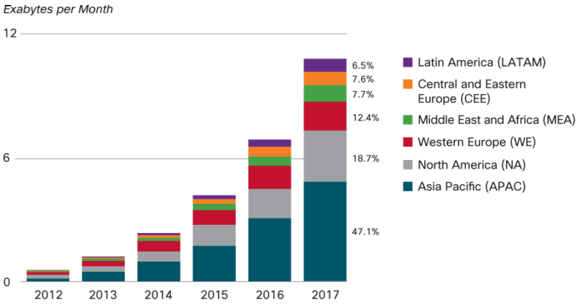
Growth of Mobile Traffic



Source: Cisco VNI Mobile Forecast, 2013

2012: 12 times the entire global internet traffic in 2000

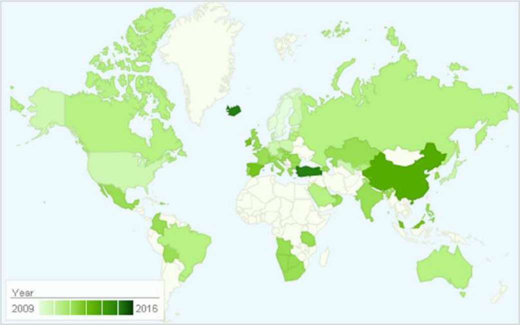
Growth of Mobile Traffic



Source: Cisco VNI Mobile Forecast, 2013

2017: 13 times higher compared to 2012

LTE Deployment



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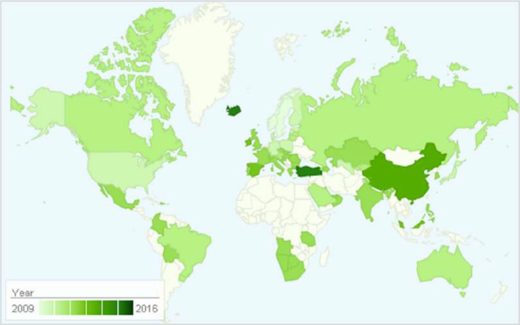
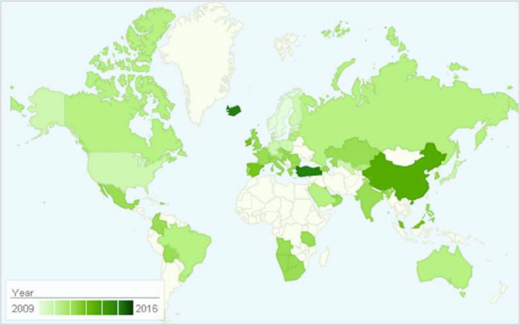


Source: Cisco, 2013

End of 2013: # of mobile connected devices > earth population

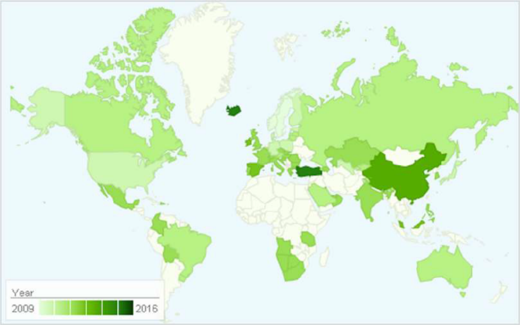
LTE Deployment



Source: Cisco, 2013

2017: 4G will represent 45% of mobile traffic

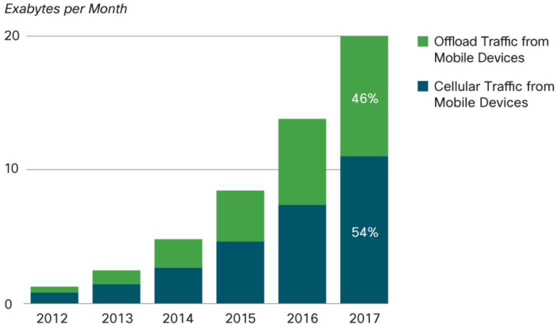
LTE Deployment



Source: Cisco, 2013

2017: 2,7 GB mobile traffic per smartphone per month

Mobile Traffic Offloading



Source: Cisco VNI Mobile Forecast, 2013

The amount of traffic offloaded from smartphones will be 46%, and the amount of traffic offloaded from tablets will be 71% in 2017 (Cisco, 2013)

90% of all cellular base stations will be small cells by 2016 (IEEE Spectrum Magazine, Informa Telecoms & Media, 2013)

Priorities

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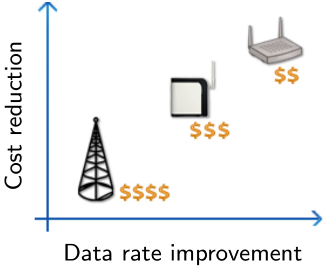
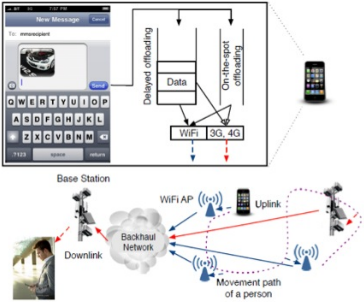
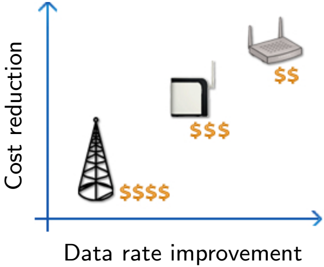
- High bandwidth
- High coverage
- Green
- Cheap

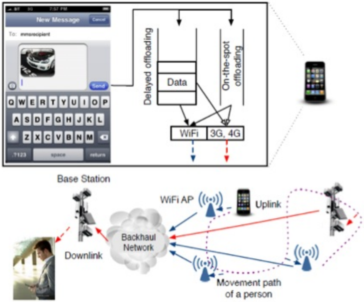
Mobile Data Offloading





Mobile Data Offloading





Are there better solutions for mobile data offloading?

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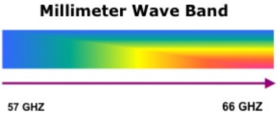
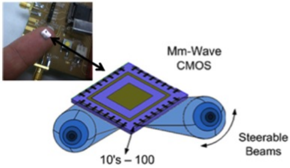
60 GHz Wireless Access Networks

- Unlicensed short range transmissions in the 60 GHz millimeter wave (mmW) band

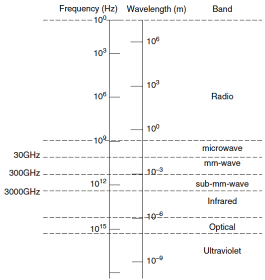


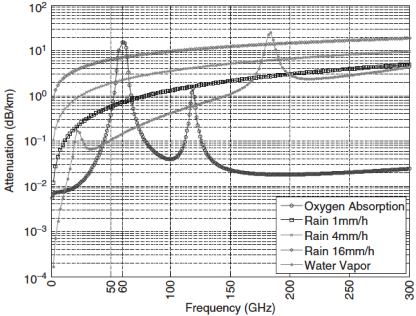
- Achieve Gbps communication
- Reduced interference
- Low-cost mmW transceivers



MillimeterWave Band

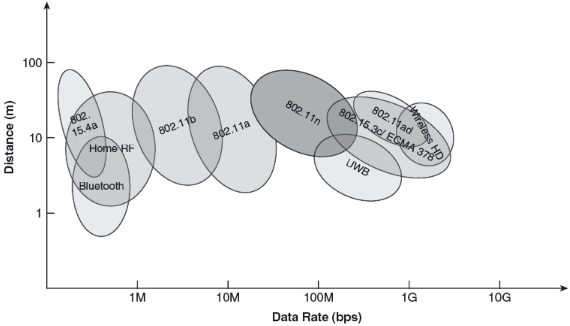
- History (J.C. Bose, 1897)
- High path loss
- High oxygen absorption





60 GHz Wireless Standards

- IEEE 802.11ad
- WiGig
- IEEE 802.15.3c
- WirelessHD
- ECMA-387



Applications

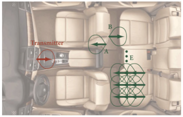
Wireless Gigabit Ethernet

Information Shower

Wireless Pills

File Transfer

In-Car Entertainment

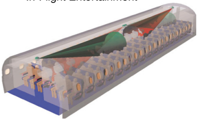


Wireless Library

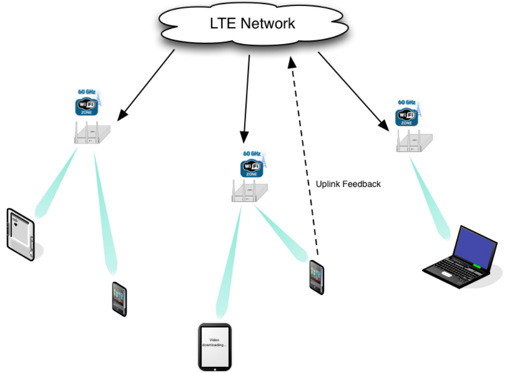
Wireless Video Cameras - Monitoring

Aircraft Structure Monitoring

In-Flight Entertainment



60 GHz to the Mobile



- 60 GHz small base stations (eg. on lamp posts)
- Downlink offload traffic in 60 GHz band with uplink LTE feedback
- 60 GHz radio on mobile device in receive-only mode

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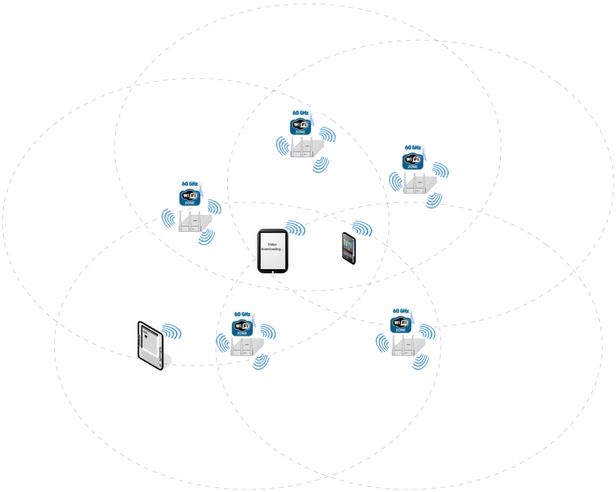
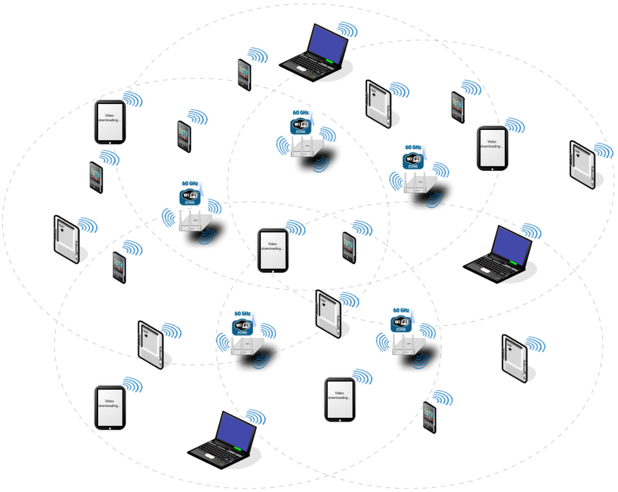


Optimizing Client Association in 60 GHz Wireless Access Networks



Optimizing Client Association in 60 GHz Wireless Access Networks

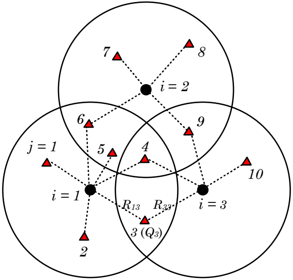
- **Goal**:
  - Distributed client association and fair load distribution
  - find the client association that minimizes the maximum AP utilization

- **Solution method**: Based on Lagrangian duality theory

- **Results**: Theoretical and numerical analysis

G. Athanasiou, P. C. Weeraddana, C. Fischione and L. Tassiulas, "Optimizing Client Association in 60 GHz Wireless Access Networks", *arXiv:1301.2723, Cornell University Library*, 2013 [Online]. Available: `http://arxiv.org/abs/1301.2723`

System Model



W	System bandwidth
P_{ij}	Transmission power of AP i to client j
G_{ij}	Power gain from AP i to client j
N_0	Power spectral density of the noise
I_j	Interference spectral density at client j
$\mathcal{M}_i$	Set of clients that can be associated to AP i
$\mathcal{N}_j$	Set of APs that client j could be associated with

- $\mathcal{N} = \{1, \ldots, N\}$ APs and $\mathcal{M} = \{1, \ldots, M\}$ clients
- Achievable rate from AP i to client $j \in \mathcal{M}_i$ is

$$R_{ij} = W \log_2 \left(1 + \frac{P_{ij} G_{ij}}{(N_0 + I_j) W} \right)$$

- Q_j is the demanded data rate of client j

System Model

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- Channel utilization between AP i and client j is

$$\beta_{ij} = \frac{Q_j}{R_{ij}}$$

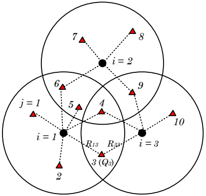
- Utilization of AP i is

$$\sum_{j \in \mathcal{M}_i} \beta_{ij} x_{ij}$$

- $(x_{ij})_{j \in \mathcal{M}_i}$ are binary decision variables, which indicate the client association

$$x_{ij} = \begin{cases} 1 & \text{if client } j \text{ is associated to AP } i \\ 0 & \text{otherwise} \end{cases}$$

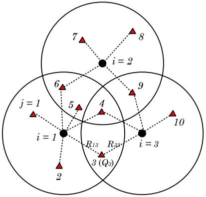
Client Association Problem Formulation



$$
\begin{aligned}
\text{minimize} \quad & \max_{i \in \mathcal{N}} \sum_{j \in \mathcal{M}_i} \beta_{ij} \ x_{ij} \\
\text{subject to} \quad & \sum_{i \in \mathcal{N}_j} x_{ij} = 1, \ j \in \mathcal{M} \\
& x_{ij} \in \{0, 1\}, \ j \in \mathcal{M}, i \in \mathcal{N}_j
\end{aligned}
$$

- Variable: $(x_{ij})_{i \in \mathcal{N}, \ j \in \mathcal{M}_i}$
- Main problem parameters: $(\beta_{ij})_{i \in \mathcal{N}, j \in \mathcal{M}_i}$, $(Q_j)_{j \in \mathcal{M}}$, $(R_{ij})_{i \in \mathcal{N}, j \in \mathcal{M}_i}$
- Constraints: a) Client j can only be assigned to one AP, b) The decision variables are binary

Equivalent Epigraph Form



$$
\begin{array}{ll}
\text{minimize} & t \\
\text{subject to} & \sum_{j \in \mathcal{M}_i} \beta_{ij} \; x_{ij} \leq t, \;\; i \in \mathcal{N} \\
& \sum_{i \in \mathcal{N}_j} x_{ij} = 1, \;\; j \in \mathcal{M} \\
& x_{ij} \in \{0,1\}, \;\; j \in \mathcal{M}, i \in \mathcal{N}_j
\end{array}
$$

- Variable: $(x_{ij})_{i \in \mathcal{N},\; j \in \mathcal{M}_i}$ and t
- Main problem parameters: $(\beta_{ij})_{i \in \mathcal{N}, j \in \mathcal{M}_i}$
- Mixed integer linear program (MILP)

Solution Method Challenges

- Existing **MILP** solvers are **centralized**
- Typically based on global branch and bound algorithms ⇒ the **worst-case complexity grows exponentially** with the problem size
- **Even small** problems, with a few tens of variables, can take a **very long time**

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- Existing **MILP** solvers are **centralized**
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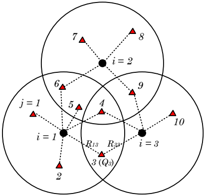
- **Even small** problems, with a few tens of variables, can take a **very long time**
- **Our approach: efficient, optimality ?**

Lagrangian Duality



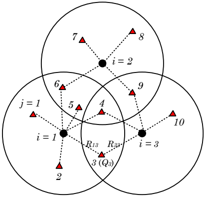
Partial Lagrangian

$$L(t, \mathbf{x}, \boldsymbol{\lambda}) = t + \sum_{i \in \mathcal{N}} \lambda_i \left(\sum_{j \in \mathcal{M}_i} \beta_{ij} x_{ij} - t \right)$$

$$= t\left(1 - \sum_{i \in \mathcal{N}} \lambda_i\right) + \sum_{j \in \mathcal{M}} \sum_{i \in \mathcal{N}_j} \beta_{ij} \lambda_i x_{ij}$$

$\boldsymbol{\lambda} = (\lambda_i)_{i \in \mathcal{N}}$: multipliers for the first set of inequality constraints

Lagrangian Duality



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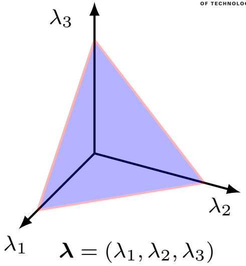
$\boldsymbol{\lambda} = (\lambda_i)_{i \in \mathcal{N}}$: multipliers for the first set of inequality constraints

Dual function

$$g(\boldsymbol{\lambda}) = \inf_{\substack{t \in \mathbb{R} \\ \mathbf{x} \in \mathcal{X}}} L(t, \mathbf{x}, \boldsymbol{\lambda})$$

$$\mathcal{X} = \left\{ \mathbf{x} = (x_{ij})_{j \in \mathcal{M}, i \in \mathcal{N}_j} \,\middle|\, \sum_{i \in \mathcal{N}_j} x_{ij} = 1,\ x_{ij} \in \{0, 1\},\ j \in \mathcal{M}\ i \in \mathcal{N}_j \right\}.$$

Lagrangian Duality



Dual problem

$$\begin{array}{ll} \text{maximize} & g(\boldsymbol{\lambda}) = \sum_{j \in \mathcal{M}} g_j(\boldsymbol{\lambda}) \\ \text{subject to} & \sum_{i \in \mathcal{N}} \lambda_i = 1 \\ & \lambda_i \geq 0, \ i \in \mathcal{N} \end{array}$$

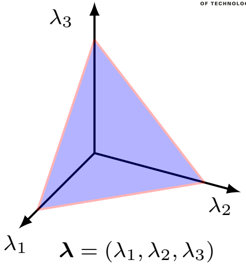
- variables: $\boldsymbol{\lambda} = (\lambda_i)_{i \in \mathcal{N}}$
- $g_j(\boldsymbol{\lambda})$ is the optimal value of the **subproblem**

$$\begin{array}{ll} \text{minimize} & \sum_{i \in \mathcal{N}_j} \beta_{ij} \lambda_i x_{ij} \\ \text{subject to} & \mathbf{x}_j \in \mathcal{X}_j \ , \end{array}$$

with the variable $\mathbf{x}_j$. Solved @ client j

Lagrangian Duality

Dual problem



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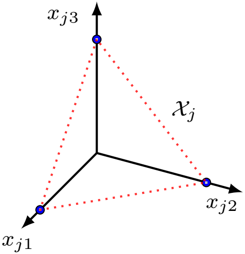

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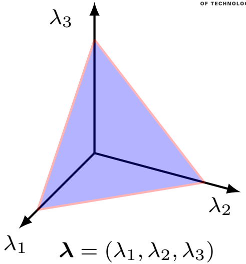
$\mathbf{x}_j = (x_{j1}, x_{j2}, x_{j3})$

Lagrangian Duality



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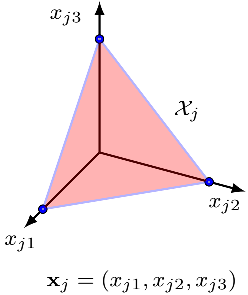

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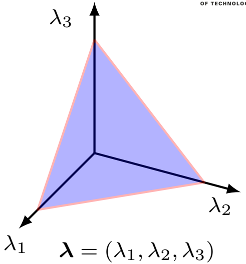

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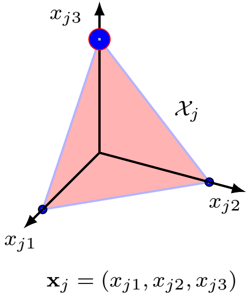

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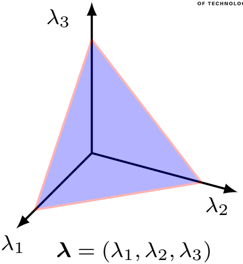

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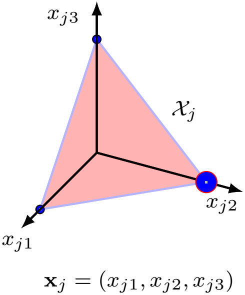

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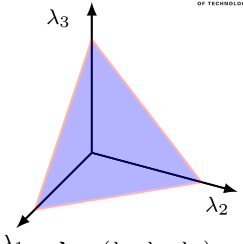

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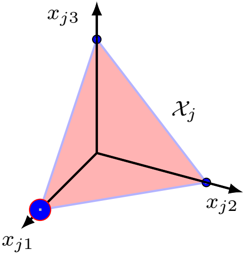
with the variable $\mathbf{x}_j$. Solved @ client j



$\mathbf{x}_j = (x_{j1}, x_{j2}, x_{j3})$

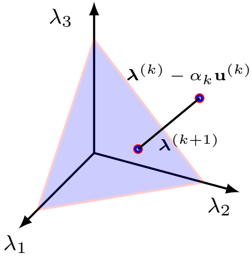
Subgradient Method

Proj. subgradient method to the dual problem

$$\boldsymbol{\lambda}^{(k+1)} = P\big(\boldsymbol{\lambda}^{(k)} - \alpha_k \mathbf{u}^{(k)}\big)$$

- P: Euclidean projection onto the unit simplex

$$\Pi = \{\boldsymbol{\lambda} | \ \sum_{i \in \mathcal{N}} \lambda_i = 1, \lambda_i \geq 0\}$$



- $\alpha_k > 0$ is the kth step size
- $\mathbf{u}^{(k)} = \left(u_i^{(k)}\right)_{i \in \mathcal{N}}$: a subgradient of $-g$ at $\boldsymbol{\lambda}^{(k)}$, where

$$u_i^{(k)} = -\sum_{j \in \mathcal{M}_i} \beta_{ij} x_{ij}^{\star} \ ,$$

and $(x_{ij}^{\star})_{j \in \mathcal{M}_i}$ is the solution of the ith subproblems with $\boldsymbol{\lambda} = \boldsymbol{\lambda}^{(k)}$

Subgradient Method

Proj. subgradient method to the dual problem

$$\boldsymbol{\lambda}^{(k+1)} = P\big(\boldsymbol{\lambda}^{(k)} - \alpha_k \mathbf{u}^{(k)}\big)$$

→ **price update**

- P: Euclidean projection onto the unit simplex

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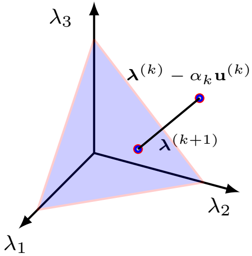

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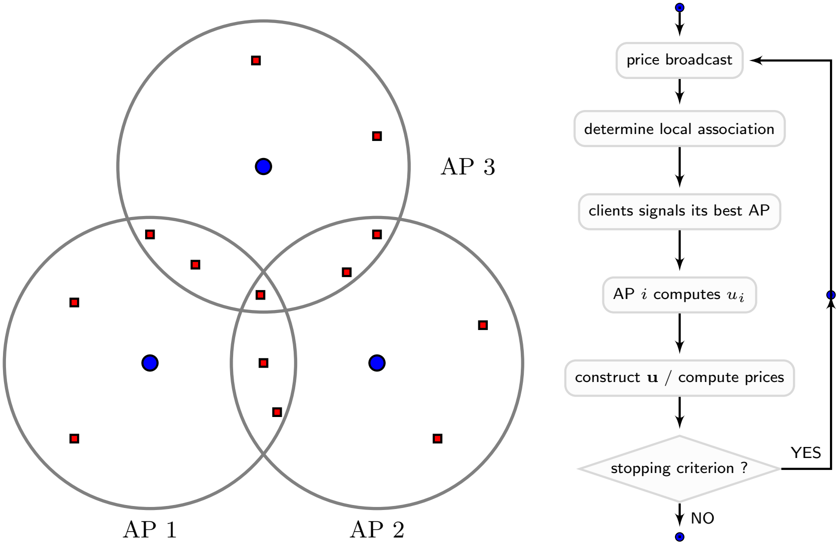
Outline

ROYAL INSTITUTE OF TECHNOLOGY

- Past, Present and Future in wireless communications
- 60 GHz millimeterWave wireless technology
- Optimizing resource allocation
- **Distributed client association (DAA)**
- Numerical analysis of DAA
- Conclusions and open research topics

DAA Illustration



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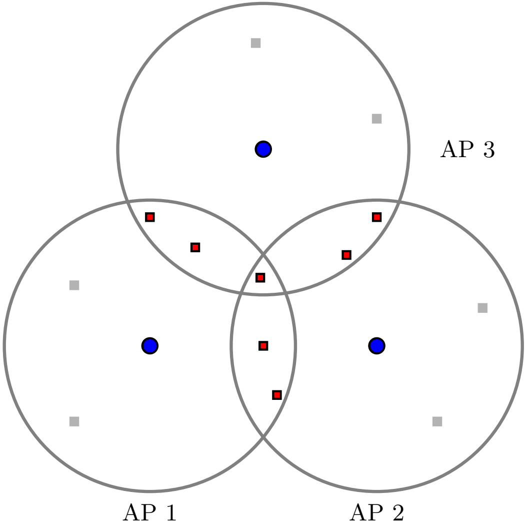

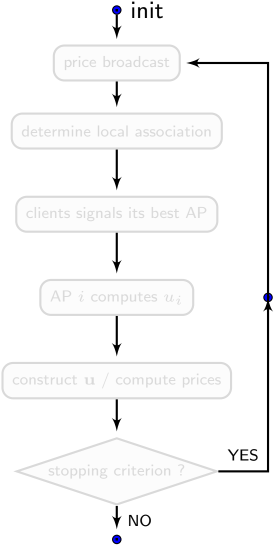

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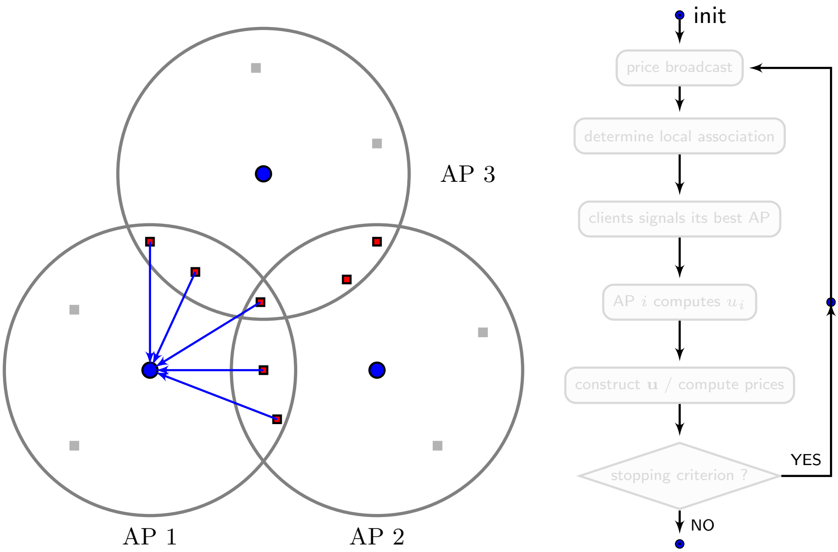

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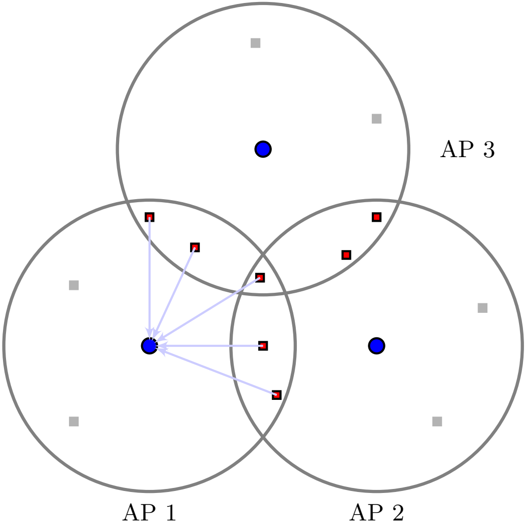

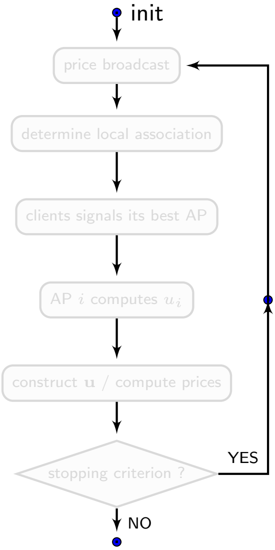

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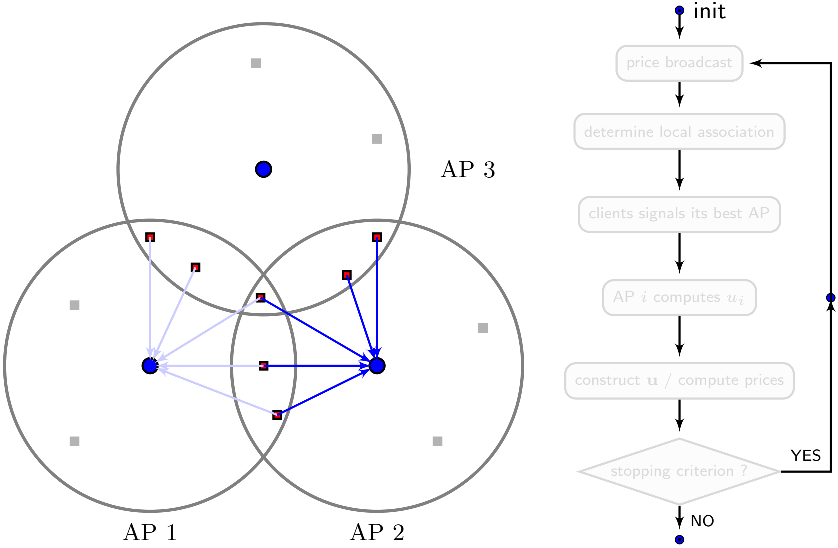

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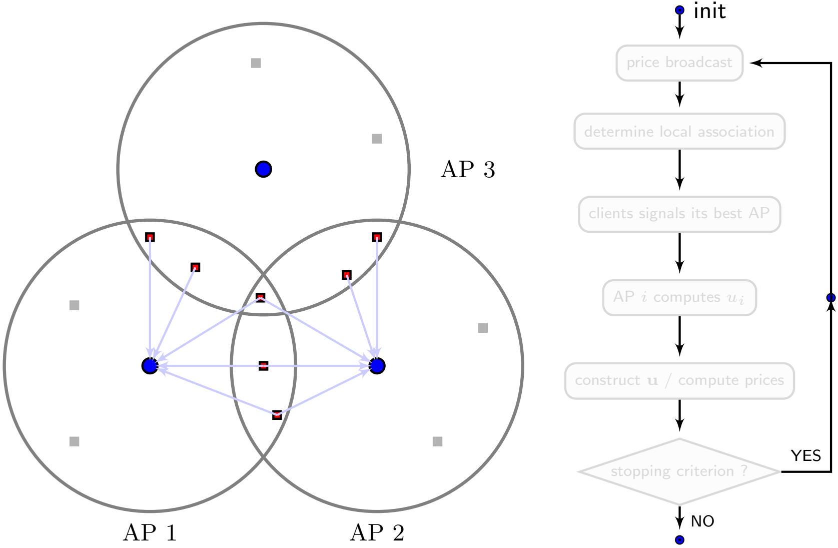

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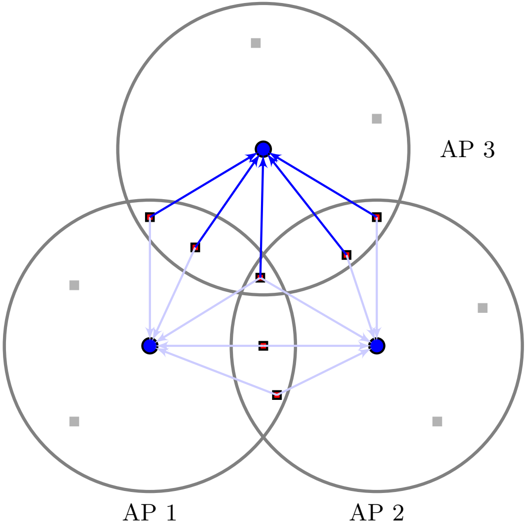

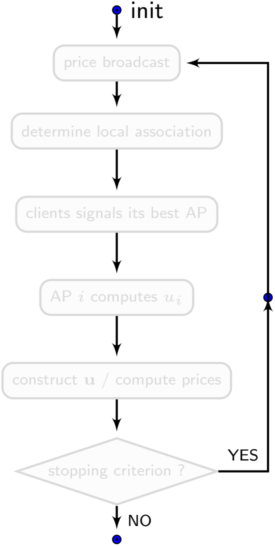

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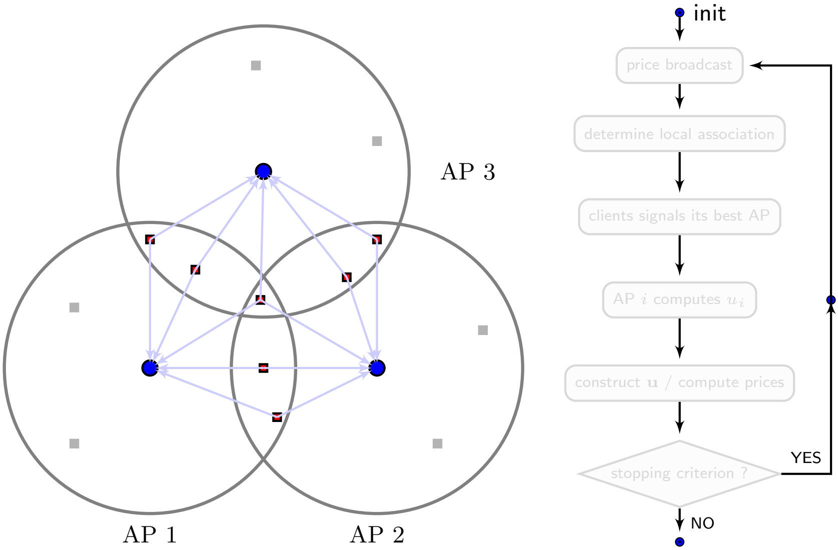

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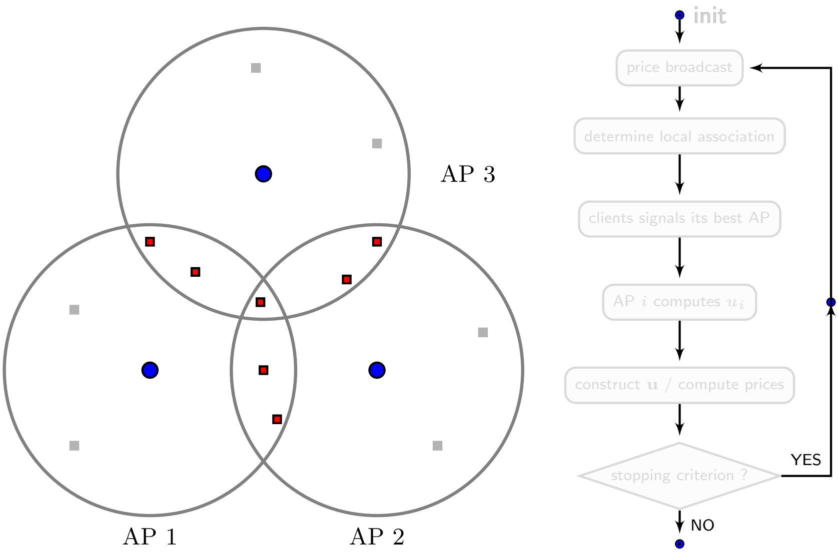

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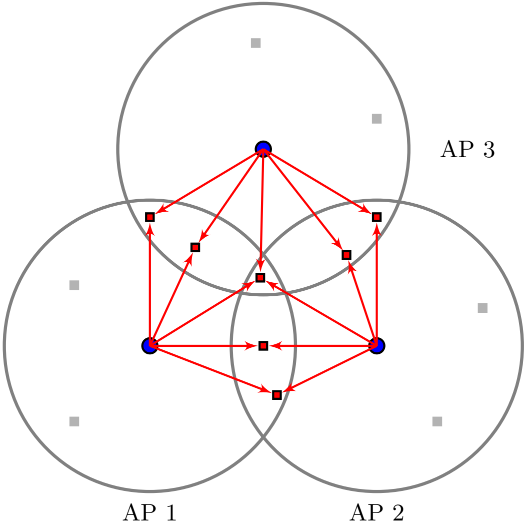

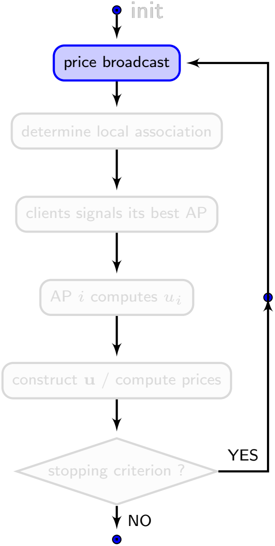

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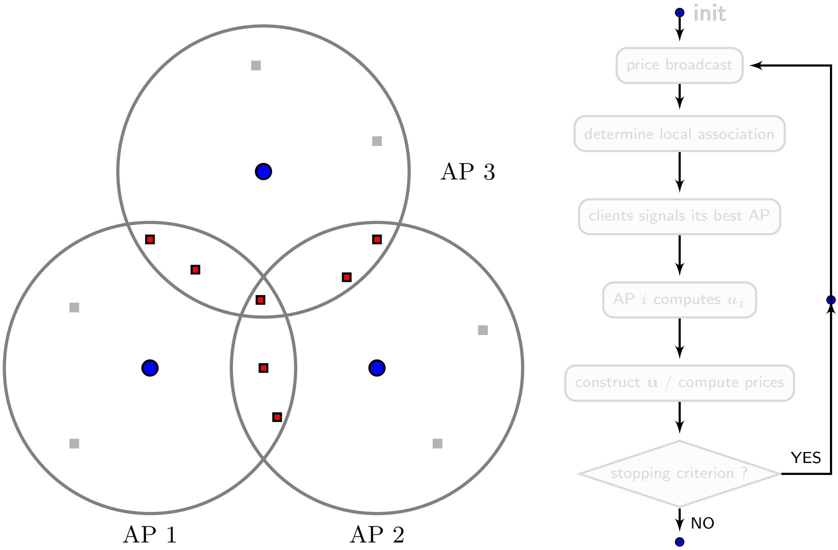

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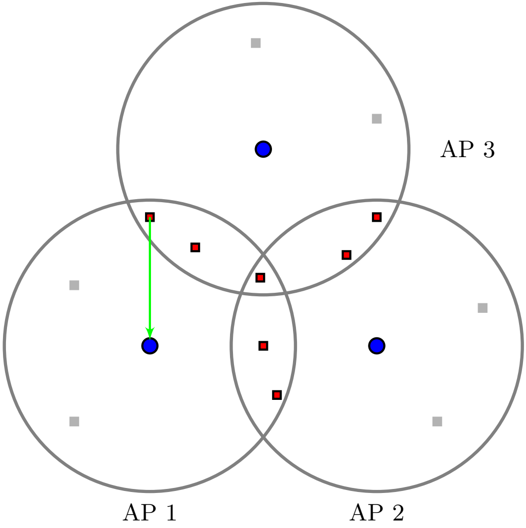

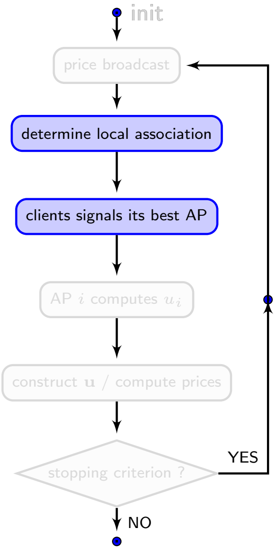

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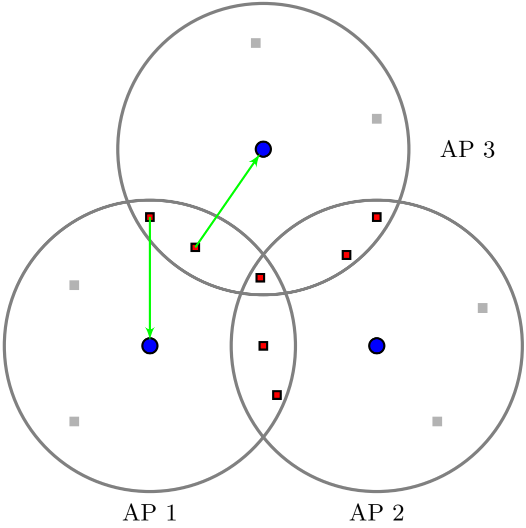

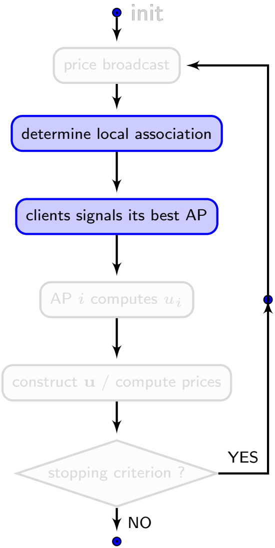

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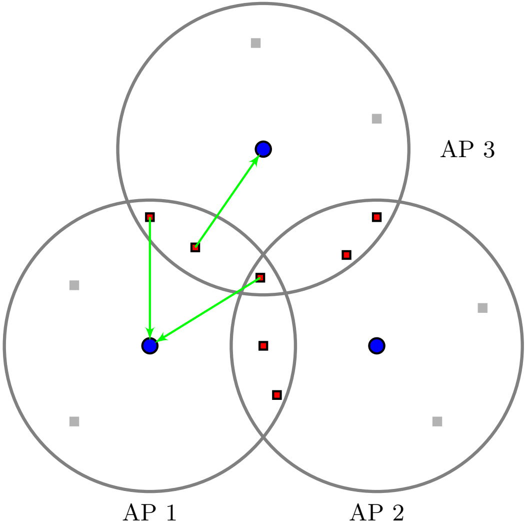

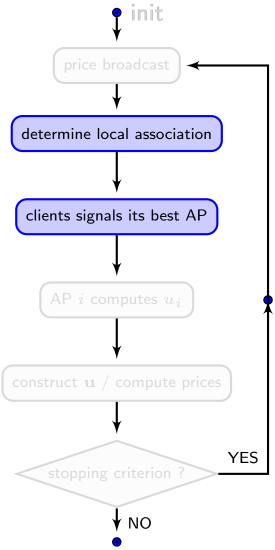

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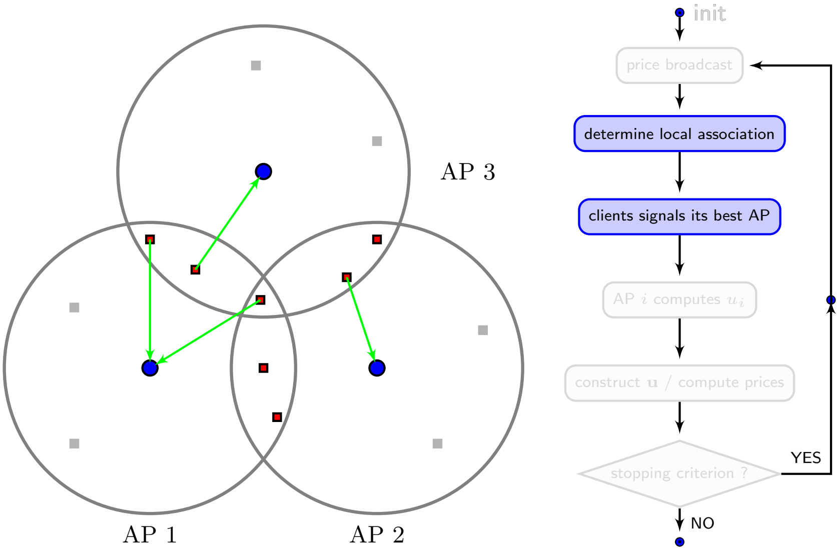

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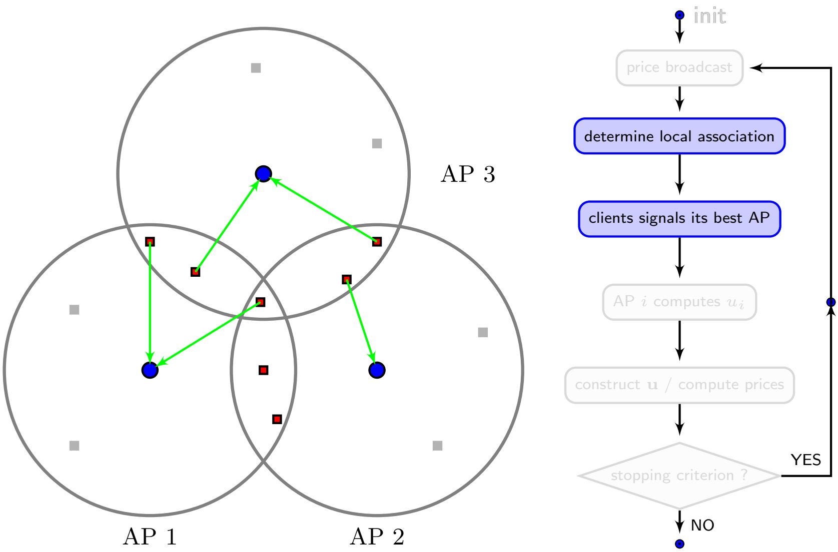

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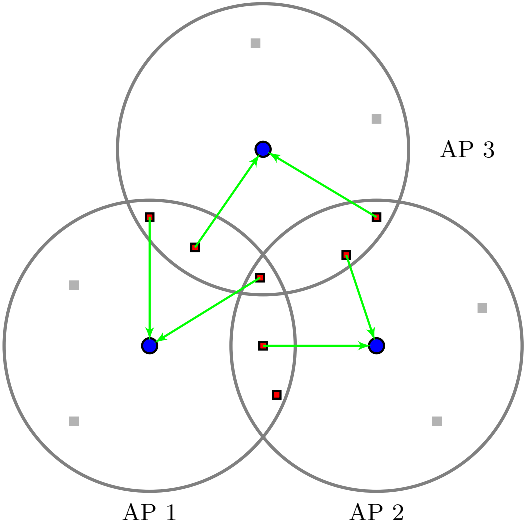

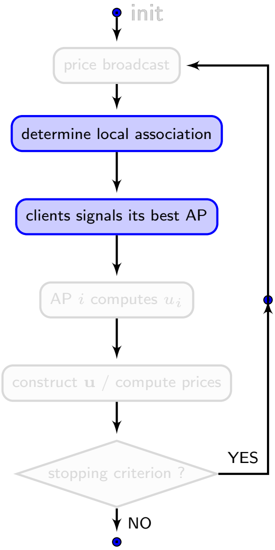

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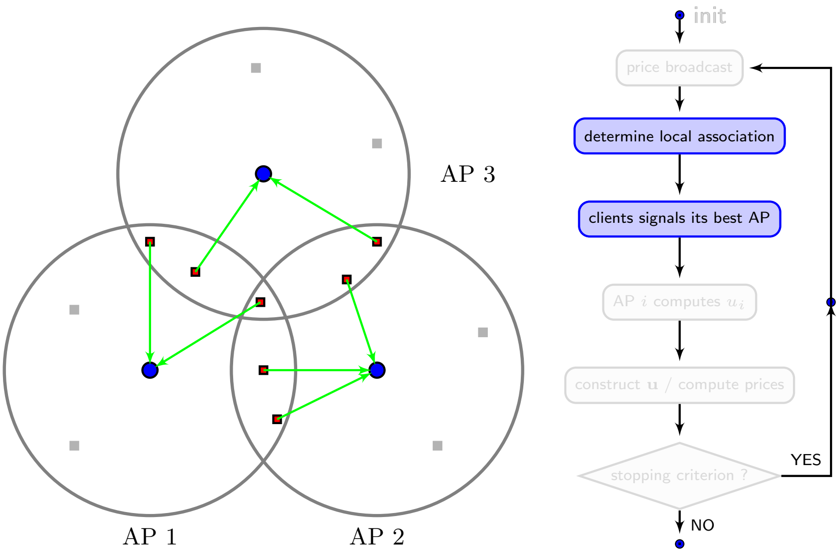

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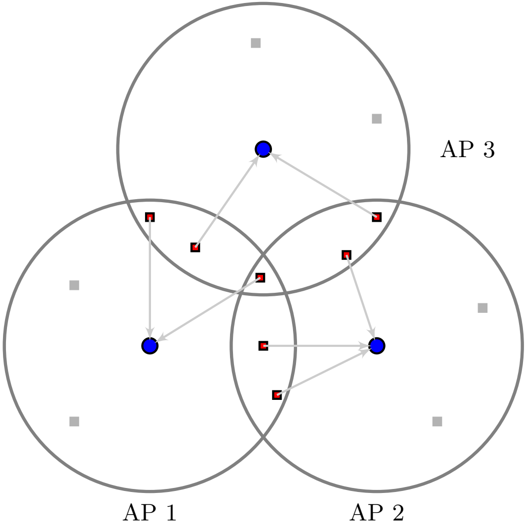

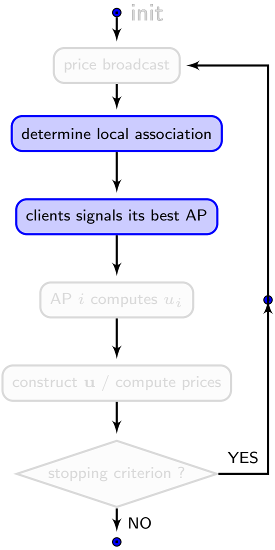

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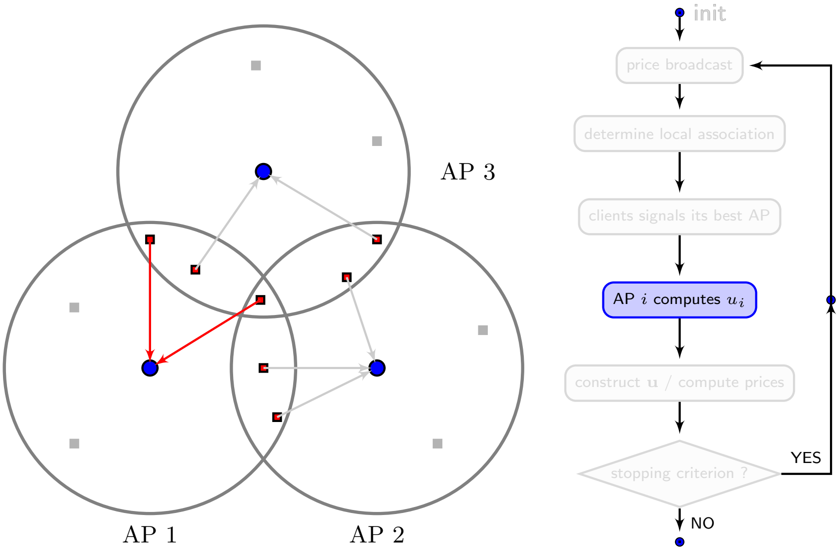

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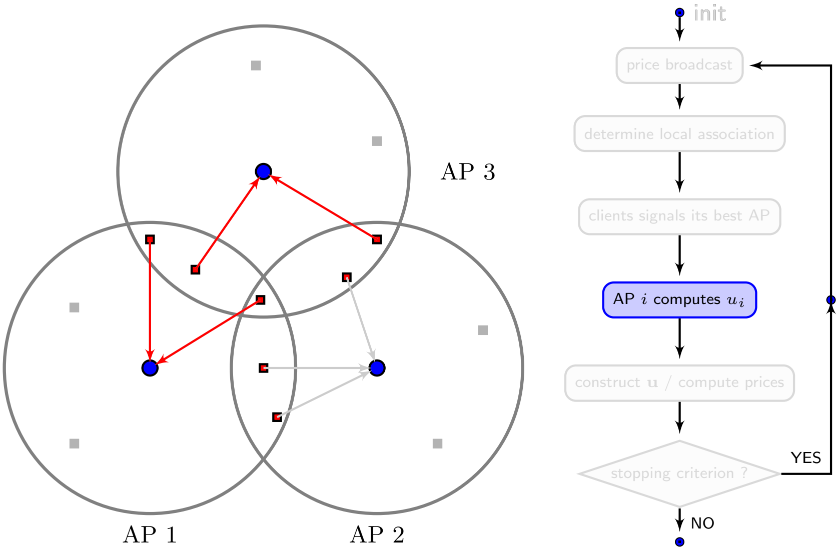

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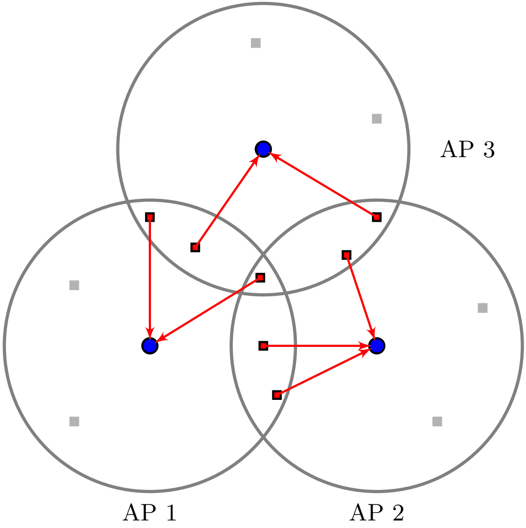

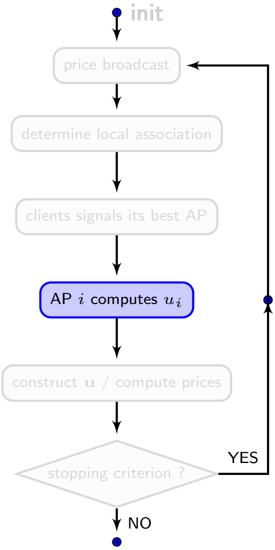

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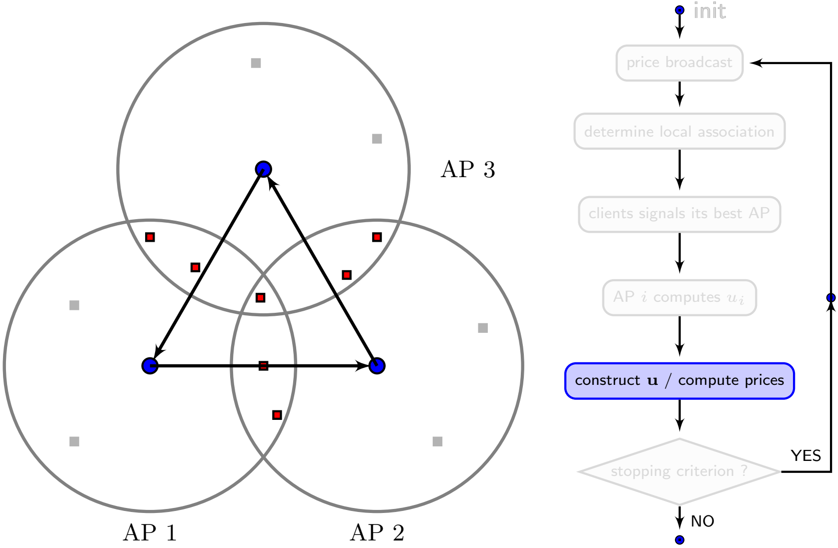

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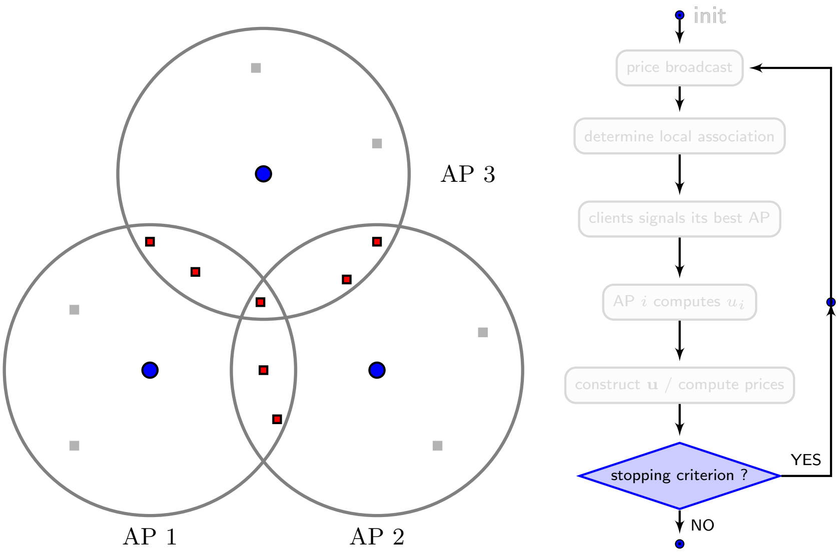

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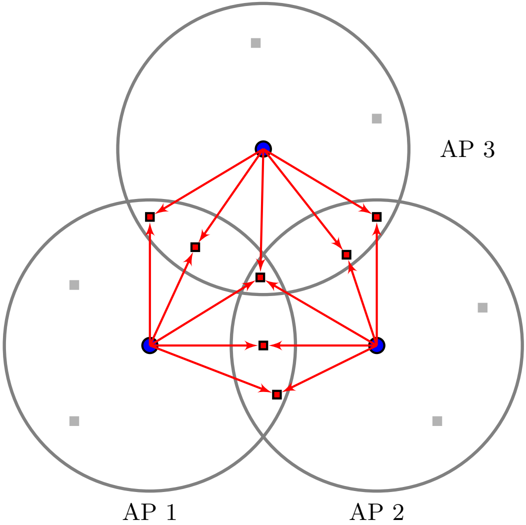

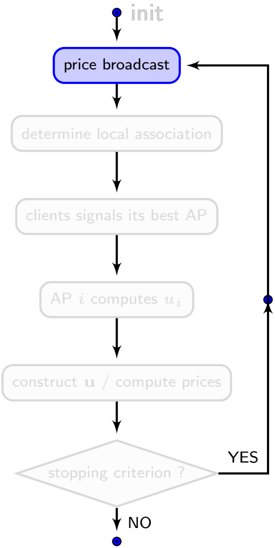

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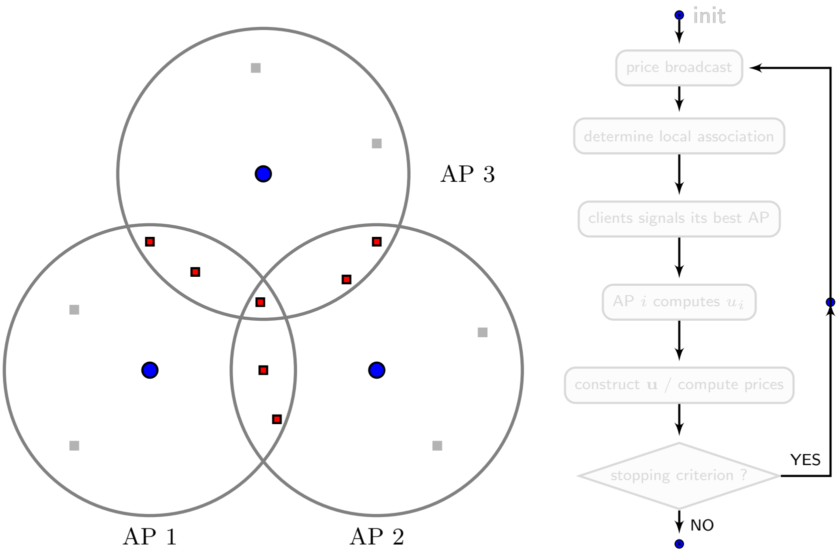

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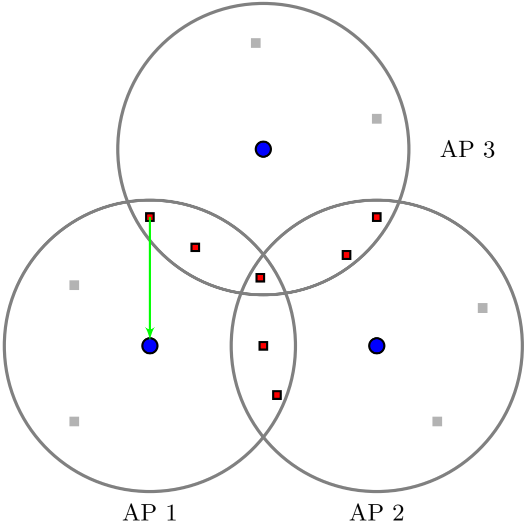

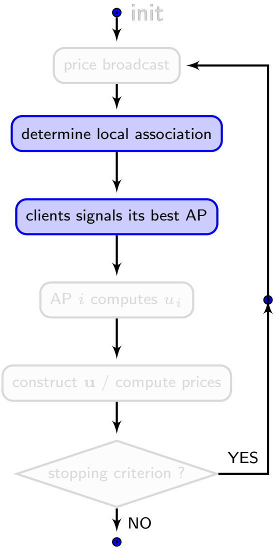

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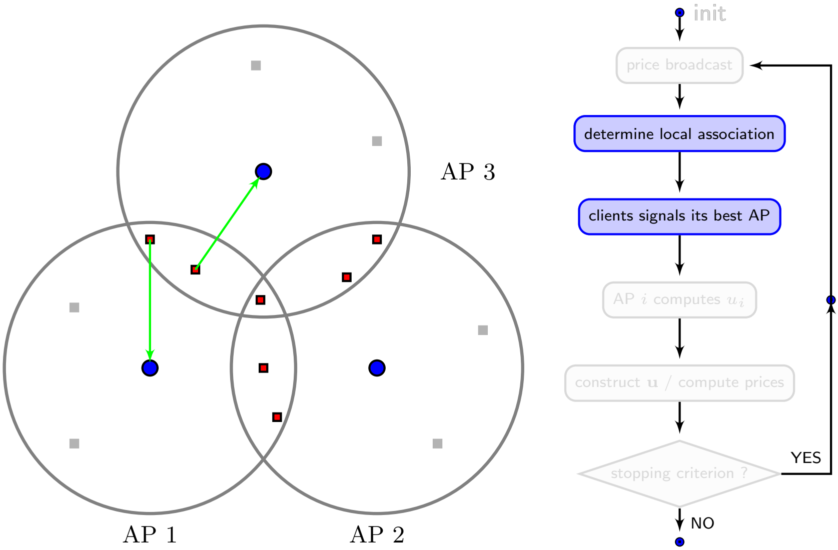

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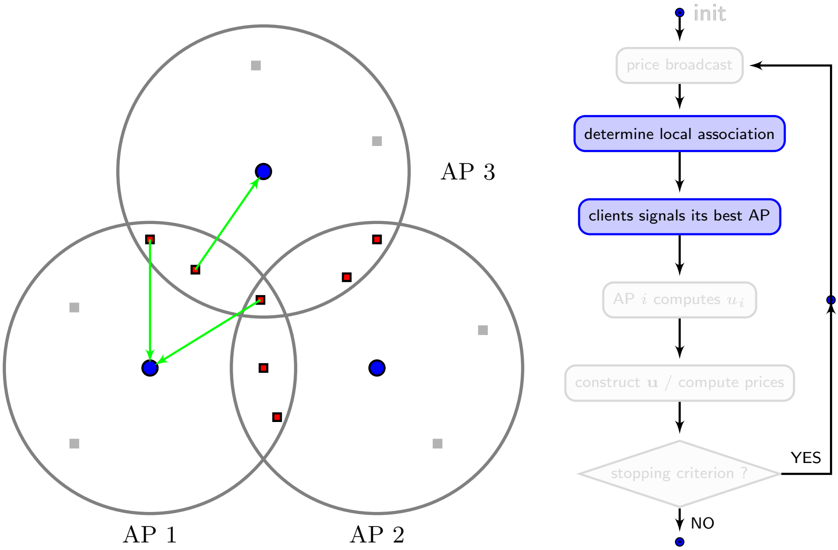

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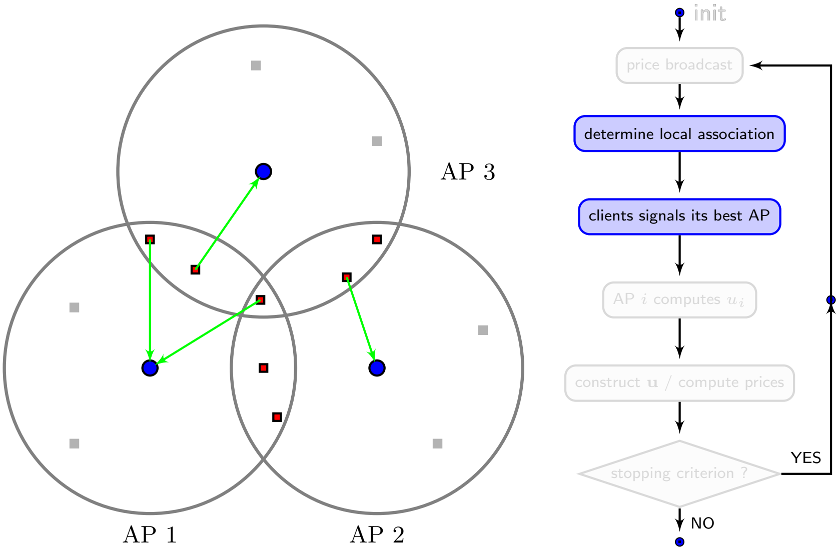

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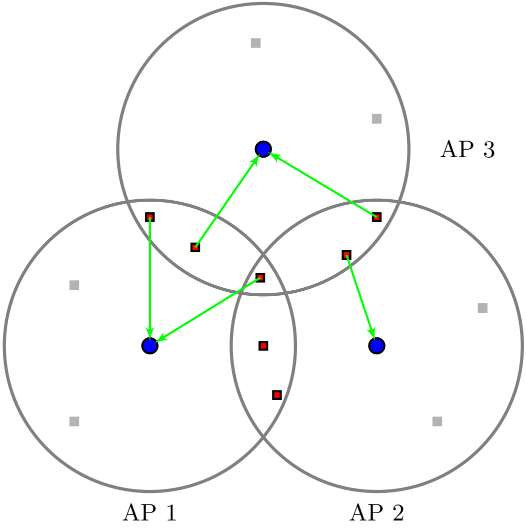

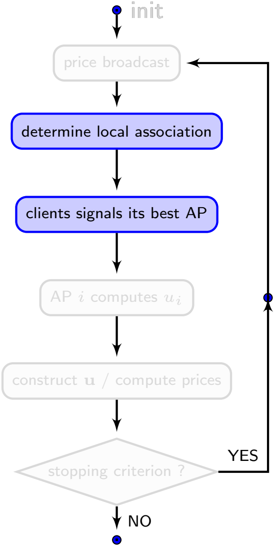

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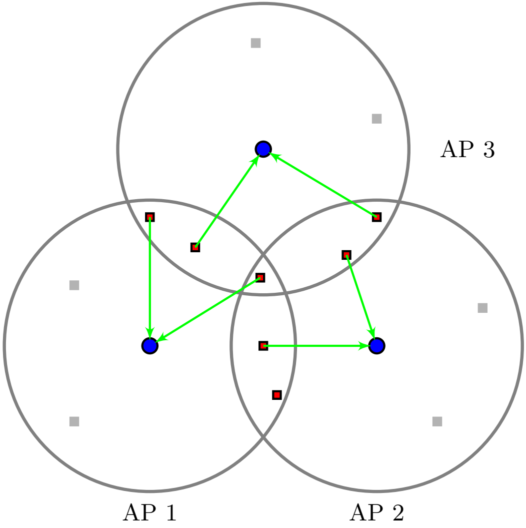

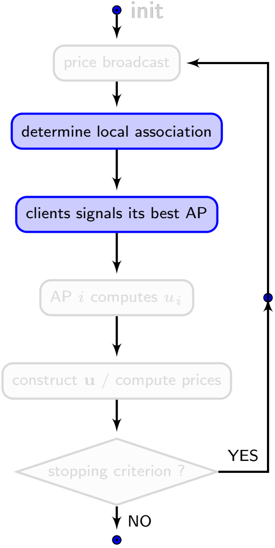

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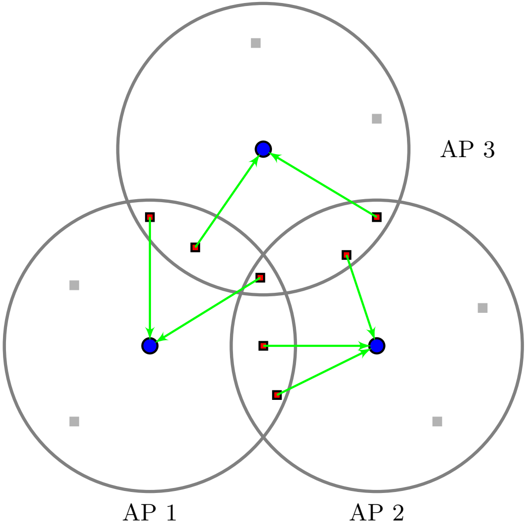

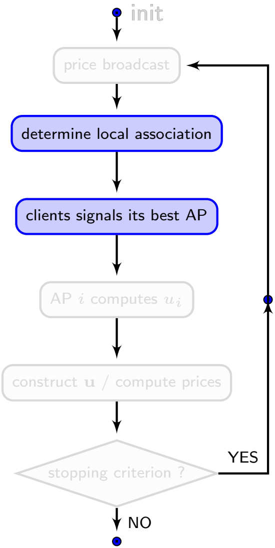

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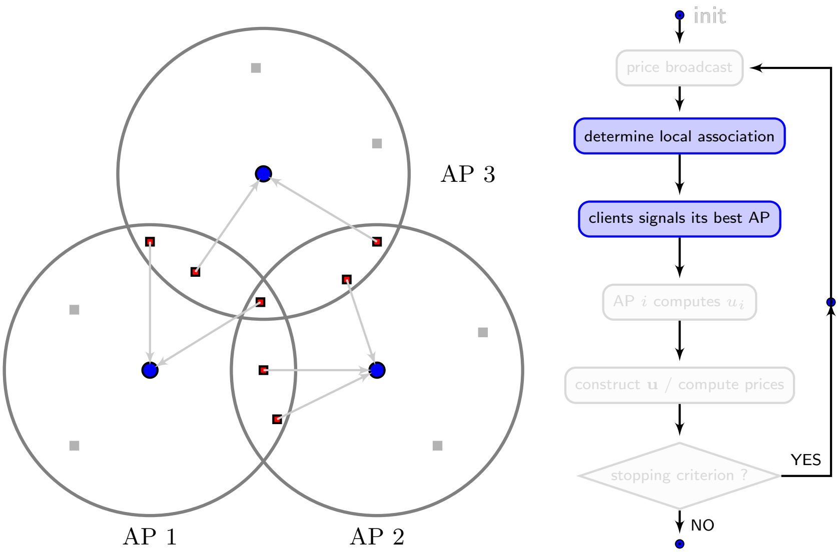

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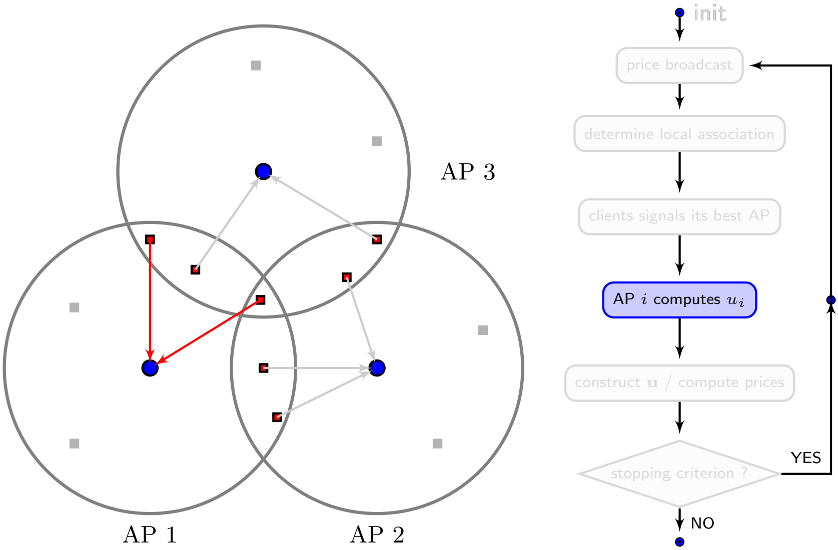

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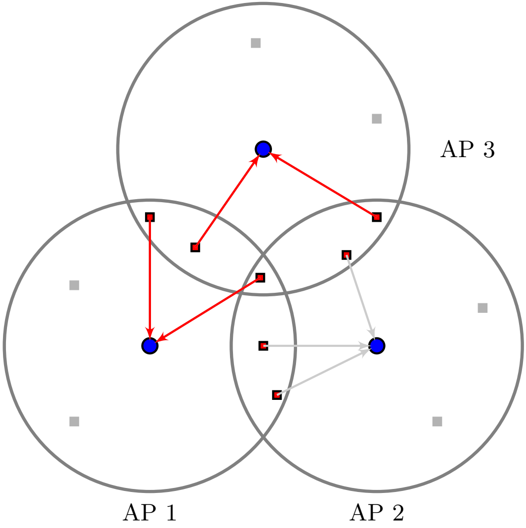

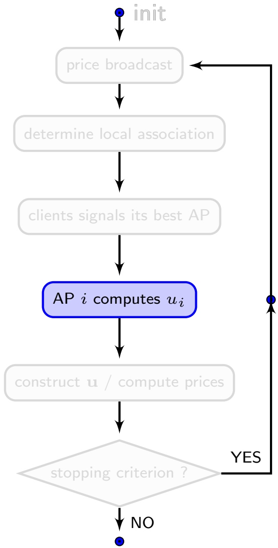

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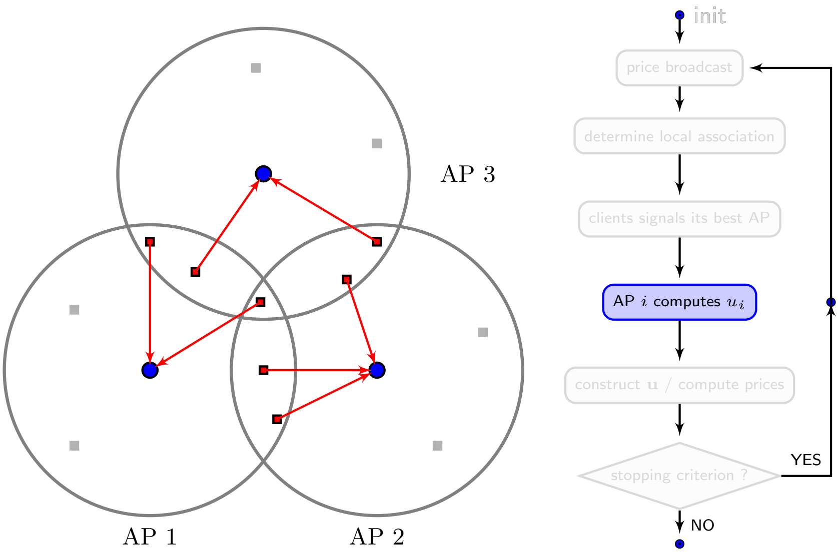

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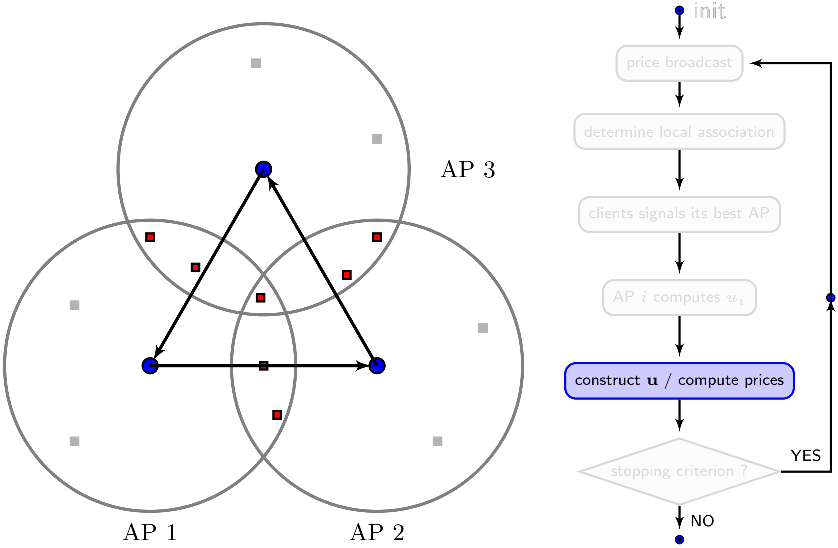

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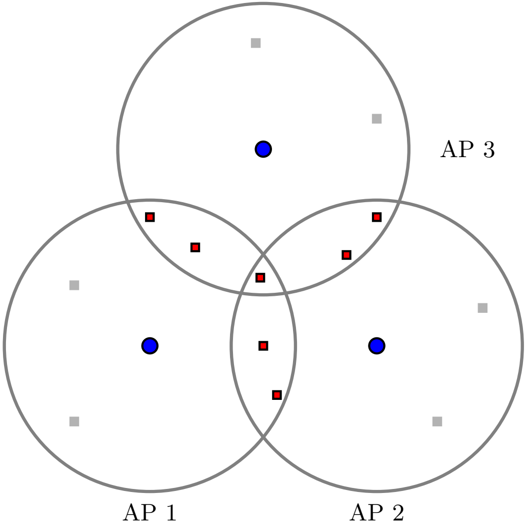

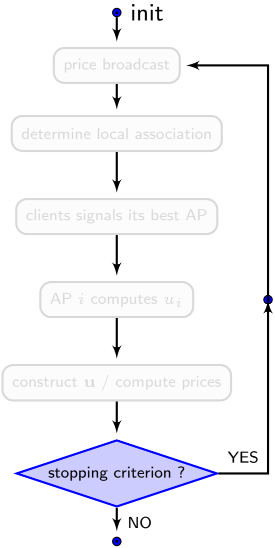

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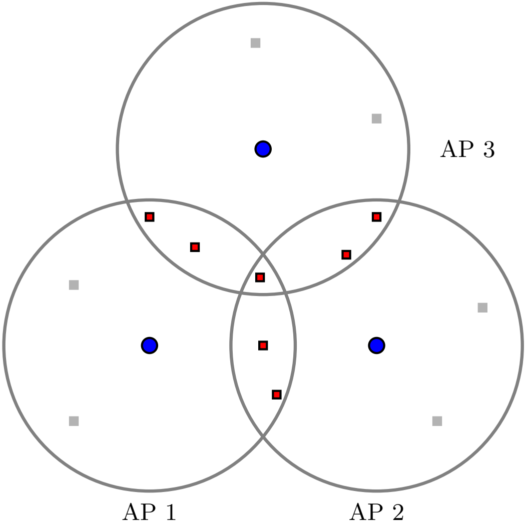
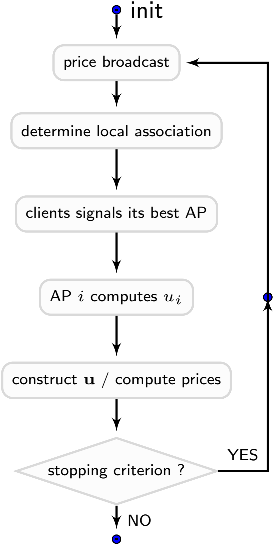




DAA Properties

Proposition (Convergence)

Let $g_{\text{best}}^{(k)}$ *denote the best dual objective value found after* k *subgradient iterations, i.e.,* $g_{\text{best}}^{(k)} = \max\{g(\boldsymbol{\lambda}^{(1)}), \ldots, g(\boldsymbol{\lambda}^{(k)})\}$*. Then,* $\forall \epsilon > 0\ \exists n \geq 1$ *such that* $\forall k\ k \geq n \Rightarrow \left(d^\star - g_{\text{best}}^{(k)}\right) < \epsilon$*.*

Proof.

Standard convergence proof for the projected subgradient method [Boy07, § 3.2][Ber99] □

DAA Properties

Theorem (Constant Duality Gap and Relative Duality Gap)

The optimal duality gap of the mixed integer linear program is bounded as follows:

$$p^\star - d^\star \leq (N+1)(\varrho + \max_{j\in\mathcal{M}} \varrho_j) \ ,$$

where $\varrho = \max_{i\in\mathcal{N}, j\in\mathcal{M}_i} \beta_{ij}$ *and* $\varrho_j = \min_{i\in\mathcal{N}_j} \beta_{ij}$. *Moreover, the relative duality gap* $(p^\star - d^\star)/p^\star$ *diminishes to* 0 *as* $M \to \infty$.

Proof.

Here we capitalized on

- the equivalent problem reformulations
- the separability of the problem
- problem's geometry

The essential guide lines are provided in [Ber98, § 5.6.1] □

DAA Properties

$$
\begin{array}{ll}
\text{minimize} & \sum_{j\in\mathcal{M}} f_j(\mathbf{y}_j) \\
\text{subject to} & \mathbf{y}_j \in \mathcal{Y}_j \ , \ j \in \mathcal{M} \\
 & \sum_{j\in\mathcal{M}} \mathbf{h}_j(\mathbf{y}_j) - \mathbf{b} \leq \mathbf{0} \ ,
\end{array}
$$

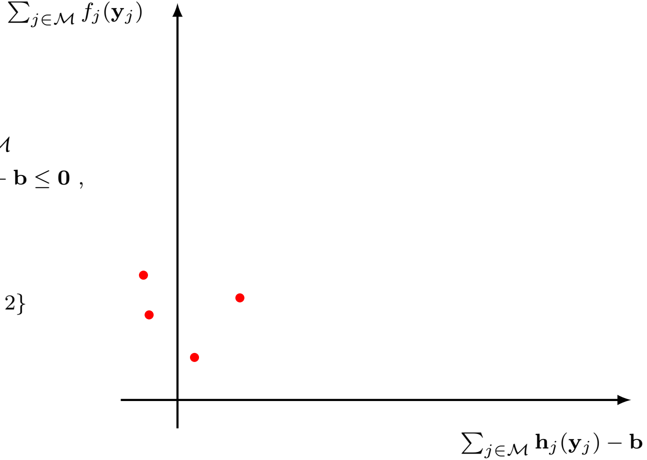
variables: $\mathbf{y}_j$.

DAA Properties

minimize $\sum_{j\in\mathcal{M}} f_j(\mathbf{y}_j)$
subject to $\mathbf{y}_j \in \mathcal{Y}_j\ ,\ j \in \mathcal{M}$
$\sum_{j\in\mathcal{M}} \mathbf{h}_j(\mathbf{y}_j) - \mathbf{b} \le \mathbf{0}\ ,$

variables: $\mathbf{y}_j$.

e.g. 1: $\mathcal{Y}_j = \{0,1\}$, $\mathcal{M} = \{1,2\}$

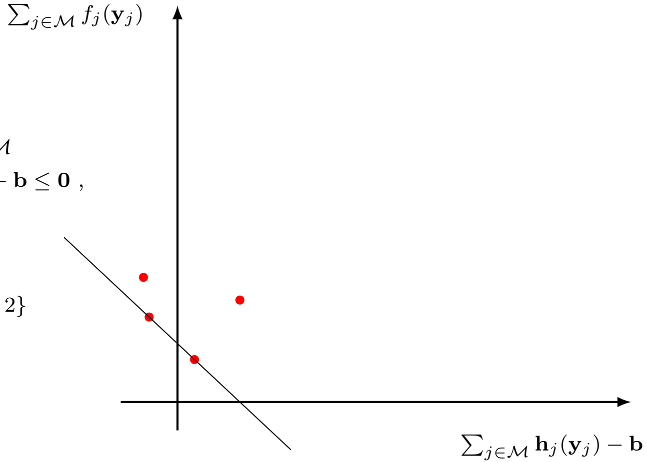


DAA Properties

minimize $\sum_{j\in\mathcal{M}} f_j(\mathbf{y}_j)$
subject to $\mathbf{y}_j \in \mathcal{Y}_j \ , \ j \in \mathcal{M}$
$\sum_{j\in\mathcal{M}} \mathbf{h}_j(\mathbf{y}_j) - \mathbf{b} \preceq \mathbf{0}$,

variables: $\mathbf{y}_j$.

e.g. 1: $\mathcal{Y}_j = \{0,1\}$, $\mathcal{M} = \{1,2\}$



DAA Properties

minimize $\sum_{j\in\mathcal{M}} f_j(\mathbf{y}_j)$
subject to $\mathbf{y}_j \in \mathcal{Y}_j \ , \ j \in \mathcal{M}$
$\sum_{j\in\mathcal{M}} \mathbf{h}_j(\mathbf{y}_j) - \mathbf{b} \leq \mathbf{0}$,

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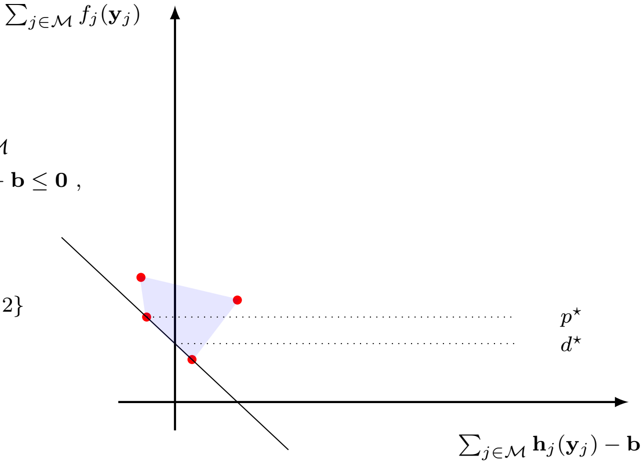

DAA Properties

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subject to $\mathbf{y}_j \in \mathcal{Y}_j \;,\; j \in \mathcal{M}$
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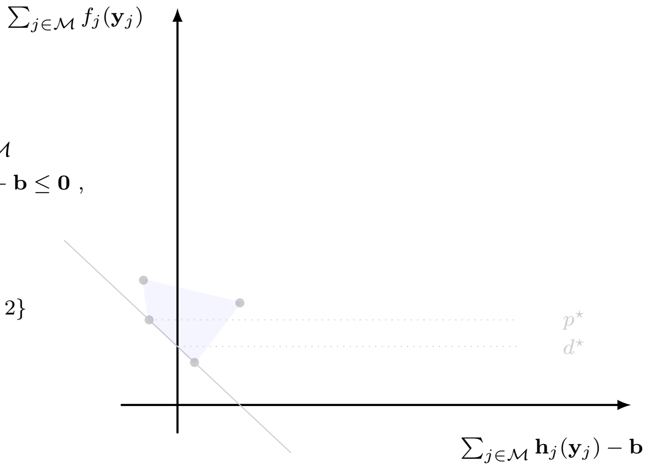


DAA Properties

minimize $\sum_{j\in\mathcal{M}} f_j(\mathbf{y}_j)$

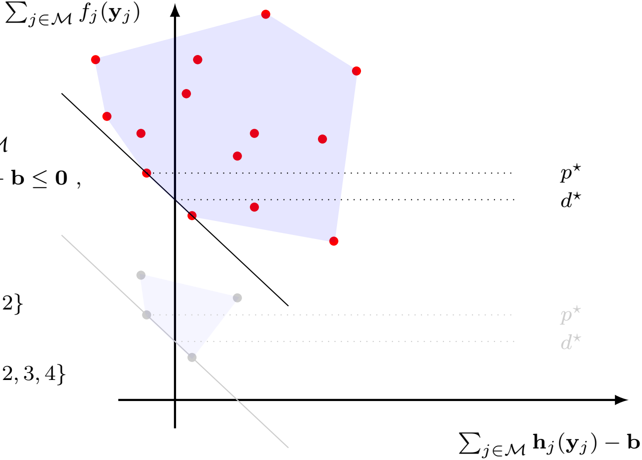
subject to $\mathbf{y}_j \in \mathcal{Y}_j \ , \ j \in \mathcal{M}$

$\sum_{j\in\mathcal{M}} \mathbf{h}_j(\mathbf{y}_j) - \mathbf{b} \leq \mathbf{0} \ ,$

variables: $\mathbf{y}_j$.

e.g. 1: $\mathcal{Y}_j = \{0,1\}$, $\mathcal{M} = \{1,2\}$

e.g. 2: $\mathcal{Y}_j = \{0,1\}$, $\mathcal{M} = \{1,2,3,4\}$



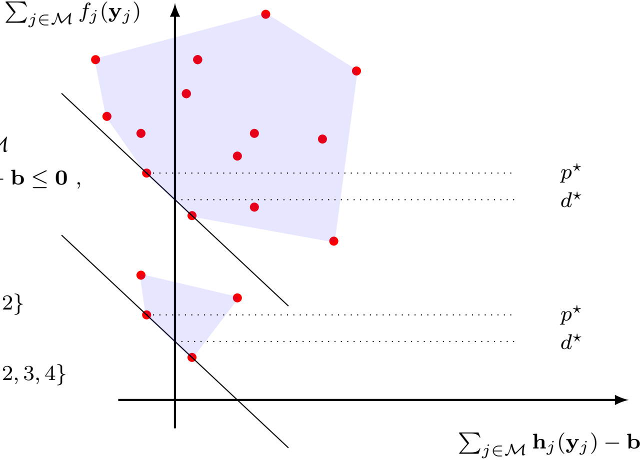
DAA Properties

minimize $\sum_{j\in\mathcal{M}} f_j(\mathbf{y}_j)$
subject to $\mathbf{y}_j \in \mathcal{Y}_j \ , \ j \in \mathcal{M}$
$\sum_{j\in\mathcal{M}} \mathbf{h}_j(\mathbf{y}_j) - \mathbf{b} \leq \mathbf{0}$,

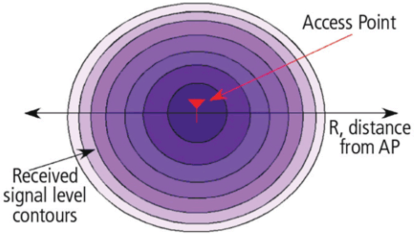
variables: $\mathbf{y}_j$.

e.g. 1: $\mathcal{Y}_j = \{0,1\}$, $\mathcal{M} = \{1,2\}$

e.g. 2: $\mathcal{Y}_j = \{0,1\}$, $\mathcal{M} = \{1,2,3,4\}$



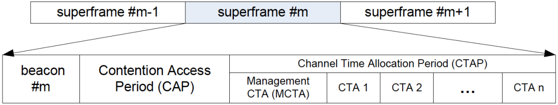
Implementation Over Existing Standards

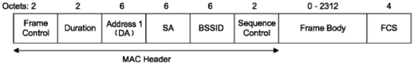


- Initially the clients follow the RSSI-based association policy that IEEE 802.11ad and IEEE 802.15.3c define

- **DAA** is periodically executed to correct possible suboptimal client associations by reallocating the available resources

Implementation Over Existing Standards





- APs trigger the initialization of **DAA** by setting a special bit into the beacon frame
- Information exchange is performed through the control frames or piggy-backing the data frames

Outline

ROYAL INSTITUTE OF TECHNOLOGY

- Past, Present and Future in wireless communications
- 60 GHz millimeterWave wireless technology
- Optimizing resource allocation
- Distributed client association (DAA)
- **Numerical analysis of DAA**
- Conclusions and open research topics

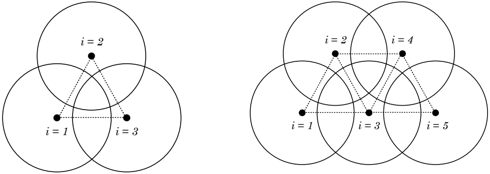
Numerical Analysis

- Consider a multi-user multi-cell environment

- Compare **DAA** to
  - Random association
  - RSSI-based association (IEEE 802.11)
  - Optimal association (IBM CPLEX)

- Measure
  - Convergence
  - Scalability
  - Efficiency (time)
  - Fairness

Topologies



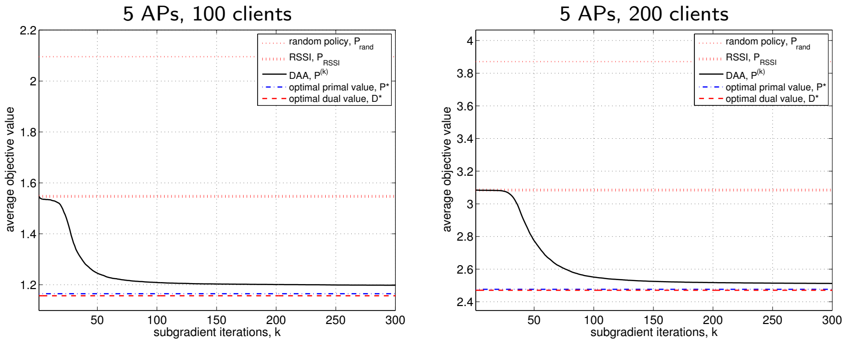
λ	Wavelength
d_0	Far field reference distance
η	Path loss exponent

- SNR operating point at a distance d from any AP

$$\texttt{SNR}(d) = \begin{cases} P_0\lambda^2/(16\pi^2 N_0 W) & d \leq d_0 \\ P_0\lambda^2/(16\pi^2 N_0 W)\cdot(d/d_0)^{-\eta} & \text{otherwise} \end{cases}$$

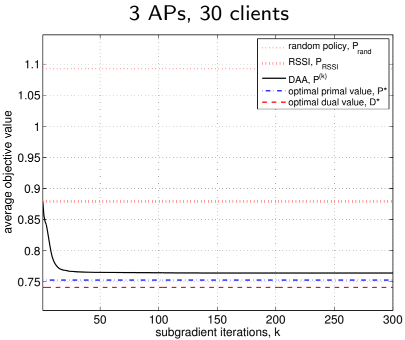
- Radius of each cell r is chosen such that $\texttt{SNR}(r) = 10$ dB
- Clients are uniformly distributed at random, among the circular cells

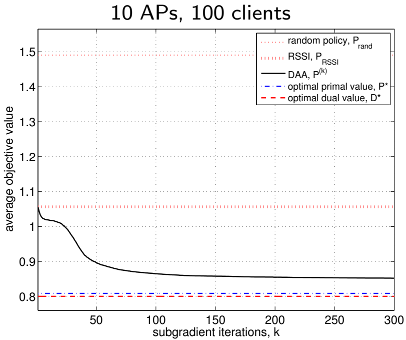
Convergence of DAA



- Average primal objective value from **DAA** after k subgradient iterations: $\mathtt{P}^{(k)} = (1/\bar{T}) \sum_{T=1}^{\bar{T}} p_{\text{best}}^{(k)}(T)$
- Average dual optimal value by **DAA**: $\mathtt{D}^{\star} = (1/\bar{T}) \sum_{T=1}^{\bar{T}} d^{\star}(T)$

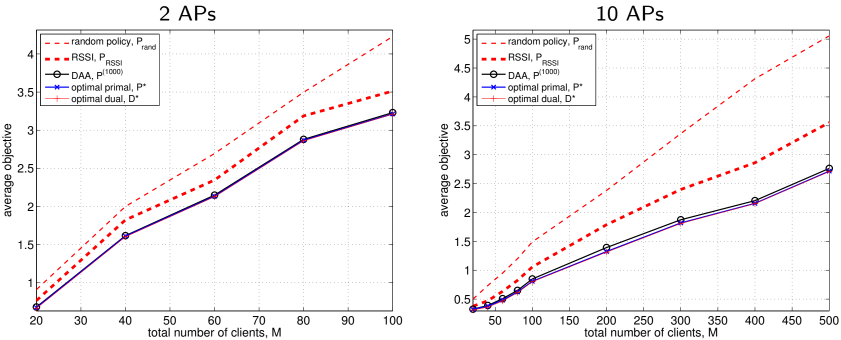
Convergence of DAA





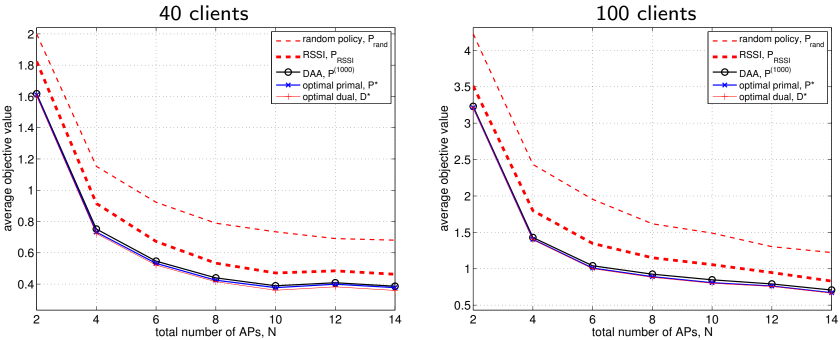
- Convergence time is affected by the number of APs and clients: The smaller the network, the faster **DAA** converges

Scalability of DAA



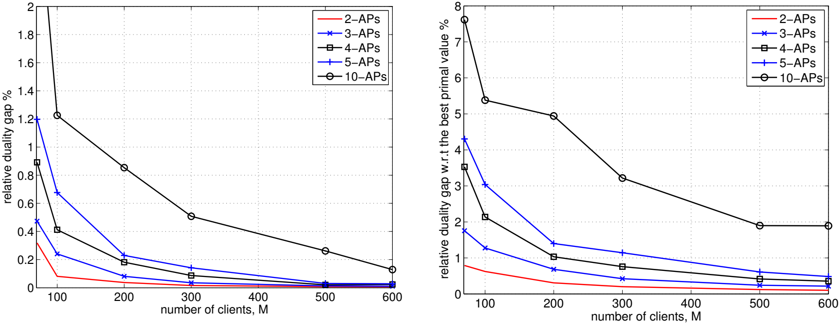
- **DAA** performs close to optimal

Scalability of DAA



- Considering constant load, the average objective value decreases while the number of APs increases
- **DAA** performs close to optimal

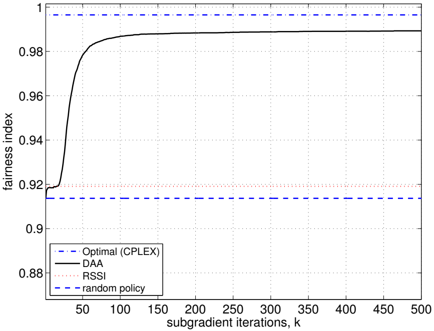
Optimality of DAA



- Average relative duality gap:
  $\texttt{Ave-RDG} = (1/\bar{T})\sum_{T=1}^{\bar{T}}(p^\star(T) - d^\star(T))/p^\star(T)$

- Average relative duality gap taking into account the best primal feasible objective value from **DAA** after K iterations at time slot T:
  $\texttt{Ave-RDG-best-achieved} = (1/\bar{T})\sum_{T=1}^{\bar{T}}(p_{\text{best}}^{(K)}(T) - d^\star(T))/p_{\text{best}}^{(K)}(T)$

Fairness Achieved by DAA

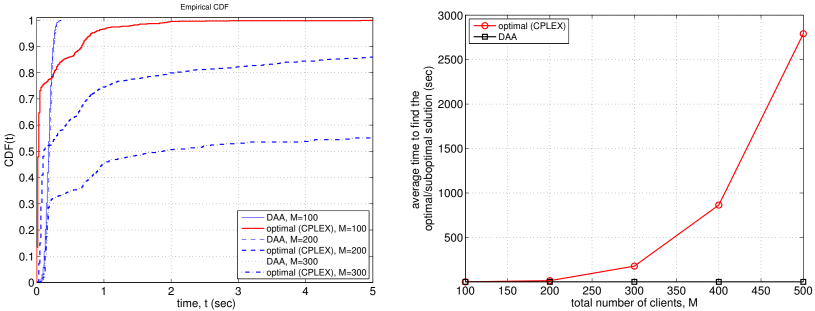


- <u>Jain's fairness index</u>:

$$J^{(k)}(T) = \Big(\sum_{i \in \mathcal{N}} Y_i^{(k)}(T)\Big)^2 / \big(N \sum_{i \in \mathcal{N}} Y_i^{(k)}(T)^2\big),$$

$Y_i^{(k)}(T) = \sum_{j \in \mathcal{M}_i} \beta_{ij} x_{ij}^{(k)}(T)$ and $x_{ij}^{(k)}(T)$ is the solution (best feasible) resulted from **DAA** at time slot T after k iterations

Speed and Resources Used by DAA



- Empirical CDF plots of the number of iterations for $M = 100, 200, 300$ clients, with $N = 10$ APs
- Trade-off between optimality and complexity

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Conclusions

ROYAL INSTITUTE OF TECHNOLOGY

- 60 GHz wireless technology: characteristics, benefits, challenges, applications
- Distributed association algorithm (**DAA**) for optimizing resource allocation in 60 GHz wireless access networks
- Performance evaluation of **DAA**: Asymptotically optimal, convergence, time efficiency and fairness
- Integration of **DAA** into current standards

Open Research Topics

- 60 GHz channel modeling
- Medium Access Control (MAC)
- Connectivity maintenance, blockage and directivity
- Coexistence and cooperation with existing wireless technologies
- Multi-hop communications
- ...

Thank you

Optimizing Client Association in 60 GHz Wireless Access Networks

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CWC 22.05.13

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