Fair Distributed Congestion Control with Transmit Power for Vehicular Networks

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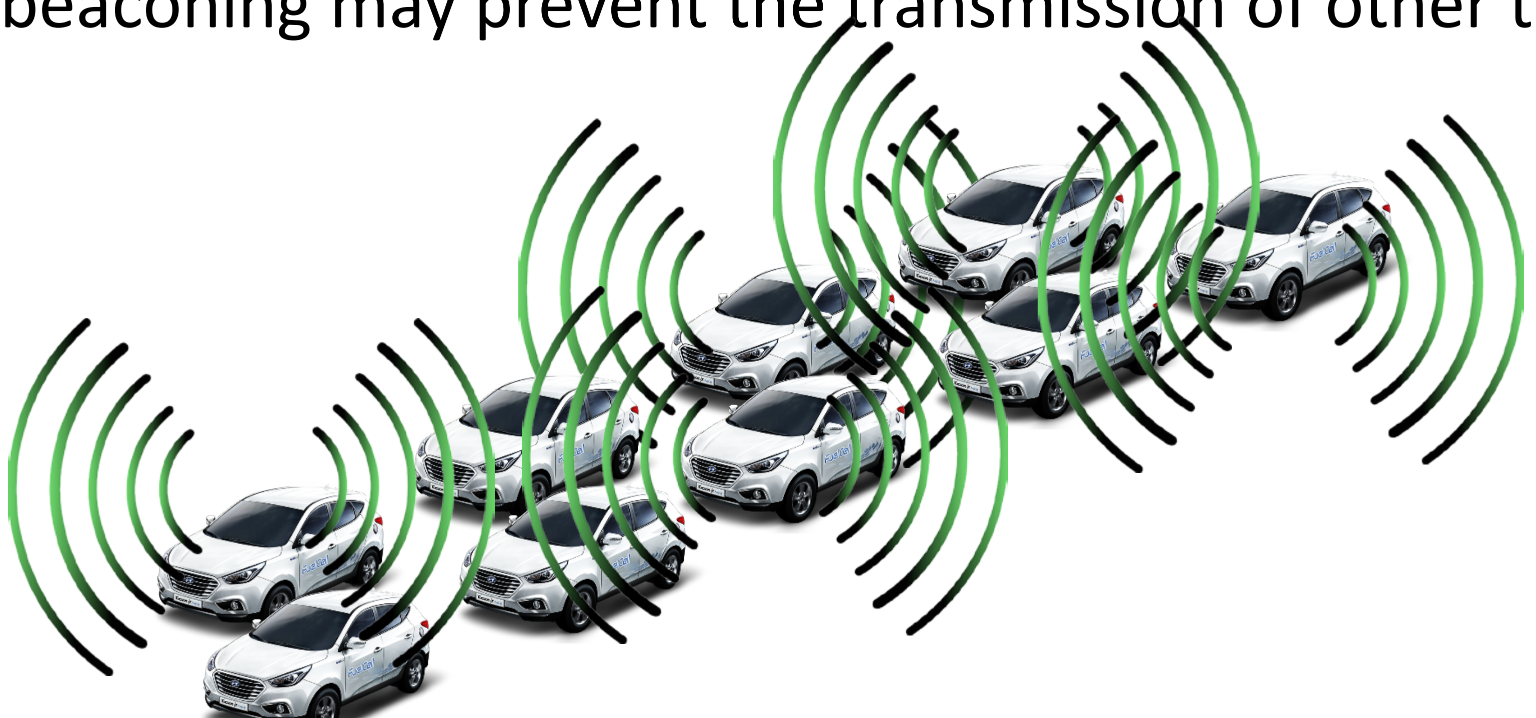
Outline

- Motivation
- Our approach: Network Utility Maximization
- Model
- Fair Distributed Congestion Control with Transmit Power (FCCP)
- Results
- Conclusions and future work

Motivation: Congestion due to beaconing

- **Beacons:** status messages broadcast periodically by vehicles
- **Awareness**: beacons make vehicles aware of other vehicles
- **Congestion** due to beaconing activity: aggregated load due to beaconing may prevent the transmission of other types of messages

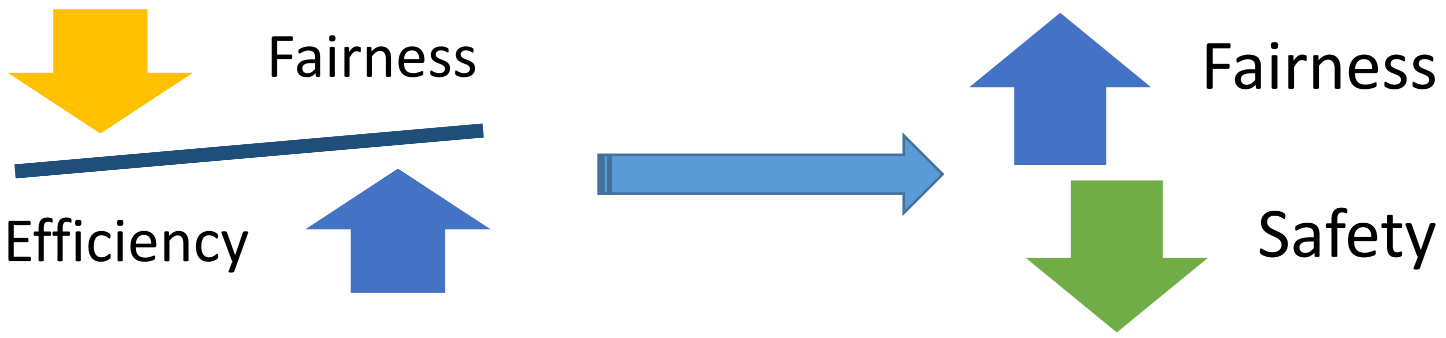


Motivation: DCC with transmit power

- **Distributed Congestion Control (DCC):** keep the channel load due to beacons under a Maximum Beaconing Load (MBL)
- How can we do it? Several **transmission parameters can be controlled**
  - beaconing rate (r_v): frequency of generation of beacons (beacons/s)
  - **transmit power (p_v)**: power used to transmit beacons (dBm)
  - data rate (d_v): speed of transmission of beacons (bps)
  - carrier sense threshold (t_v): sensitivity to measured power in channel (dBm)
  - A combination of them
- Requirements:
  - Distributed: no central controller available
  - Good adaptation capabilities: environmental conditions change quickly
  - **Fair:** resources can be shared in different ways, which have further implications

Motivation: Why is Fairness important?

- **Safety**: beacons are used to estimate the state of neighbors
  - I want others to know my state and I need to know others state
  - No vehicle should be allocated arbitrarily less resources than its neighbors
- But, **how much fairness**?
  - Different fairness notions can be defined: proportional fairness, max-min…
  - There is a **trade-off between fairness and efficiency**:
    - *"more"* fairness → less efficient use of the resource (fewer beacons/s, shorter range...)
  - **But safety benefits from efficiency:**
    - the quality of the state information depends on the beaconing rate and range…
- **Too much fairness may be detrimental to safety**



Motivation: summary of requirements

- We want our control algorithm to:
  - Keep the **beaconing load under** a selectable **MBL**
  - Be **distributed**
  - Be **fair**
  - **Select the fairness notion**
  - Seamlessly **adapt to** environmental **changes**
  - Be **dynamically** and **autonomously configurable** to particular vehicle needs
  - Use only **local information**
- Is it possible?

Our approach: Network Utility Maximization

- Network Utility Maximization (NUM):
  - A utility function is associated to each vehicle
  - Optimization problem: maximization of the sum of utilities of each vehicle
  - Subject to constraints
  - The shape of the utility function determines the induced fairness notion
- NUM has been applied in many other contexts.
  - Problem: you have to send feedback to sources. Difficult with multihop flows.
  - In vehicular networks, for DCC, it is practical because sources of congestion are in range.
- In [5], we applied NUM to control beaconing rate
- In [6], we applied NUM to control (only) beaconing rate with multiple powers
- Here, we apply NUM to control (only) **transmit power**

Model: channel, network and utility

- Propagation and fading model: single-slope path loss with Nakagami-m

Probability of received power at d above the sensitivity (S)

$$p_r(m,p) = Pr(\mathbf{F} > SAd^\beta) =$$

$$= 1 - F_{\mathbf{F}}(SAd^\beta) = \frac{\Gamma(m, \frac{SAd^\beta m}{p})}{\Gamma(m)}$$

Incomplete Gamma Function

Fading intensity (m)

- Define $p_r(m,p) = f(m, K_{ij}/p)$
- Each vehicle v ∈ V can select a transmit power $p_v \in [p_v^{min}, p_v^{max}]$
- Maximum Beaconing Load (MBL) limited to C beacons/s
- α-fair utility function U_v **ensures that the optimal solutions** to the NUM problem **are (w,α)-fair**

$$U_v(x) = \begin{cases} w_v x & \text{if } \alpha = 0 \\ w_v \log x & \text{if } \alpha = 1 \\ w_v \frac{x^{1-\alpha}}{1-\alpha} & \text{if } \alpha > 0, \alpha \neq 1 \end{cases}$$

α parameter used to select the fairness notion

Model: general problem formulation

- General transmit power optimization problem G-P

$$\mathbf{G-P}: \quad \max_{p_v} \sum_v U_v(p_v) \tag{3a}$$

Maximize the sum of the utilitities of vehicles

subject to:

$$\sum_{v'} r_{v'} f(m, K_{vv'}/p_{v'}) \leq C \quad \forall v \in V \tag{3b}$$

Average load measured by vehicles below MBL

$$p_v^{min} \leq p_v \leq p_v^{max} \quad \forall v \in V \tag{3c}$$

Optimization variable p_v between allowable limits

- G-P not convex in general!

$$p_r(m,p) = f(m, K_{ij}/p)$$

The convexity of function f depends on the value of its parameters

Model: change of variable

- G-P can be transformed into convex form by a change of variable:

$$\frac{1}{p} = y^{\frac{1}{m}}$$

New optimization variable: y

- Now $f(m, K_{ij} y^{\frac{1}{m}})$ is strictly convex for m > 0 and all y ≥ 0.

- And $U(p) = U(y^{-\frac{1}{m}}) = \frac{(y^{-\frac{1}{m}})^{1-\alpha}}{1-\alpha}$ is concave for α ≥ m +1

Only certain fairness notions can be used. For instance, for m=1 proportional fairness (α=1) would make the problem not convex

Model: Equivalent convex problem

- Convex form of the power control problem

Use of α-fair utility function $U_v(y_v)$.
Fairness notion can be selected with the value of parameter α

Maximize each vehicle power:
$p_v = y_v^{-1/m}$

$$\mathbf{C-P:}\quad \max_{y_v} \sum_v \frac{\left(y_v^{\frac{-1}{m}}\right)^{1-\alpha}}{1-\alpha} \tag{4a}$$

subject to:

$$\sum_{v'} r_{v'} f(m, K_{vv'} y_{v'}^{\frac{1}{m}}) \le C \quad \forall v \in V \tag{4b}$$

$$(p_v^{max})^{-m} \le y_v \le (p_v^{min})^{-m} \quad \forall v \in V \tag{4c}$$

Beaconing rate r_v
is not controlled. Each vehicle can autonomously set its value

Quality of service requirements of applications can be autonomously enforced by vehicles with these settings

Each vehicle can autonomously set their max and min powers

Model: solution via dual decomposition

- To find a decentralized algorithm we use a dual decomposition:
  - Form the Lagrangian L of (4a), relaxing the constraints (4b)

$$L(\lambda, y_v) = \sum_v \left(\frac{(y_v^{\frac{-1}{m}})^{1-\alpha}}{1-\alpha} - r_v(\sum_{v'} \lambda_{v'} f(m, K_{v'v} y_v^{\frac{1}{m}}) \right) + \\ + C \sum_v \lambda_v \quad (5)$$

  - λ_v are the Lagrange multipliers (prices)
  - Define the Lagrange dual, $g(\lambda)$:

$$g(\lambda) = \max_{(p_v^{max})^{-m} \leq y_v \leq (p_v^{min})^{-m}} L(\lambda, y_v) \quad (6)$$

  - And the dual problem:

$$\min_{\lambda \geq 0} g(\lambda) = \min_{\lambda \geq 0} \left\{ \max_{(p_v^{max})^{-m} \leq y_v \leq (p_v^{min})^{-m}} L(\lambda, y_v) \right\} \quad (7)$$

  - The dual approach is
    - Solve dual problem (7) by finding the optimal prices λ_v^*
    - Plug optimal prices λ_v^* in (6) and solve the optimization problem (6) to get the optimal powers p_v^*

Model: distributed algorithm

Since there are constraints for problem (7): λ ≥0, we have to project on the constraint set

- To find the optimal prices λ_v^* we use a **projected gradient algorithm**:
  - At each iteration *t*:
    - Vehicles collect the prices from their neighbors λ
    - Vehicle *v* computes its new λ_v with a gradient update step:

      $$\lambda_v(t+1) = [\lambda_v(t) - \gamma \nabla g(\lambda_v(t))]_{\lambda \geq 0}$$

- Vehicle *v* *then* plugs the prices from their neigbors λ in (6) and solves that maximization problem to obtain the next power
  - But, (6) has no analytic solution in this case
  - So, to solve maximization problem (6) we apply another projected gradient algorithm, which we call **Local Gradient Projection (LGP)**
  - $y_v(t+1) = [y_v(t) - \varepsilon \nabla L(y_v(t))]_{ymax \geq y \geq ymin}$

- So, we need $\nabla g(\lambda_v(t))$ to solve (7) and $\nabla L(y_v(t))$ to solve (6)

Fair Distributed Congestion Control with Transmit Power (FCCP)

Solves dual problem (7)

Algorithm 1 - Fair Distributed Congestion Control with Transmit Power (FCCP).

At $k = 0$, set initial vehicle price λ_v^0 and power via $p^0 = y_v^{-\frac{1}{m}}$

Then, at each time k:

Step 1. Each vehicle v receives the prices of all the neighbor vehicles $\lambda_{v'}^k$.

Step 2. Each vehicle updates its own price λ_v^{k+1} according to: $\lambda_v^{k+1} = \left[\lambda_v^k + \gamma\left(\sum_{v'} r_{v'} f(m, K_{vv'} y_{v'}^{\frac{1}{m}}) - C\right)\right]^+_{\lambda_v \geq 0}$

Step 3. Each vehicle computes y_v^{k+1} as the result of execution of Algorithm (2): $y_v^{k+1} = LGP(\lambda_{v'}^k, y_v^k, r_v)$

Transmit with power $p^{k+1} = (y_v^{k+1})^{-\frac{1}{m}}$

$\nabla g(\lambda_v(t))$ is equivalent to measuring the CBR and substracting the MBL

Only needs the collected prices from neighbors and our current power and beaconing rate

Solves problem (6)

Algorithm 2 - Local Gradient Projection with diminishing step size.

procedure LGP(λ_v, y, r)

$y^1 = y$, $i = 1$

repeat

$y^{i+1} = \left[y^i + \epsilon(i)\nabla L_{y_v}(y^i)\right]^+_{(p_v^{max})^{-m} \leq y \leq (p_v^{min})^{-m}}$

$i = i + 1$

until $|\nabla L| = 0$

return y^{i+1}

end procedure

$$\nabla L_{y_v}(y_v) = \frac{\partial L(\lambda, y_v)}{\partial y_v} =$$

$$= -\frac{y_v^{\frac{\alpha-1}{m}-1}}{m} + r_v \sum_{v'} \lambda_{v'} (K_{v'v})^m e^{-K_{v'v} y_v^{\frac{1}{m}}}, \quad \forall v \qquad (9)$$

Simple projection on the constraint set: if y ≥ ymax, then y = ymax, else if y ≤ ymin, then y=ymin

Summary and remarks about FCCP

- After a number of iterations the scheme **converges to the optimal power allocation** with the **selected fairness** notion.
  - $\lambda_v(1)$->$\lambda_v(2)$->$\lambda_v(3)$->…$\lambda_v(n)$-> λ_v^*
  - $p_v(1)$->$p_v(2)$->$p_v(3)$->…$p_v(n)$-> p_v^*
- To update the price, vehicles measure the CBR and then substract the MBL.
- Sample period (T_s): time between algorithm iterations. Used to measure CBR and collect prices from neighbors. We set it to T_s= 250 ms.
- **Minimum overhead**: a vehicle only needs to **piggyback in beacons its own price**, $\lambda_{v,}$ a real number.
- Radio channel fading (m) and path loss exponent (β) can be estimated from measurements [9].
- **Local information**: For LGP a vehicle only needs to know its current power and beaconing rate and the prices from neighbors. $K_{vv'}$ = SAm$(d_{vv'})^{\beta}$ are computed with the distance information included in beacons.
- With α we can select the desired fairness notion.
- Each vehicle can **autonomously** set its own maximum and minimum power and beaconing rate to meet its **quality of service** requirements

Results: configuration of static scenarios

Parameter	Value
Pathloss exponent (β)	2.5
Data rate (V_t)	6 Mbps
Sensitivity (S)	-92 dBm
Frequency	5.9 GHz
Noise	-110 dBm
SNIR threshold	4 dB
Beacon size (b_s)	500 bytes
Beaconing rate (r_v)	10 beacons/s
Power range ($[p_v^{min}, p_v^{max}]$)	[10, 1000] mW

- **Multihop** static scenarios for validation: 286 vehicles
  - Equally spaced (d=10 m) along 2850 m
  - Random: poisson distribution with mean 10 m.
- **Optimal**: exact solution to problem C-P (4) computed with Mathematica
- **Numerical**: FCCP implemented in Java in and ideal scenario without MAC
- **Realistic**: FCCP simulated with OMNET++ with MAC, collisions, capture effect and SINR evaluation

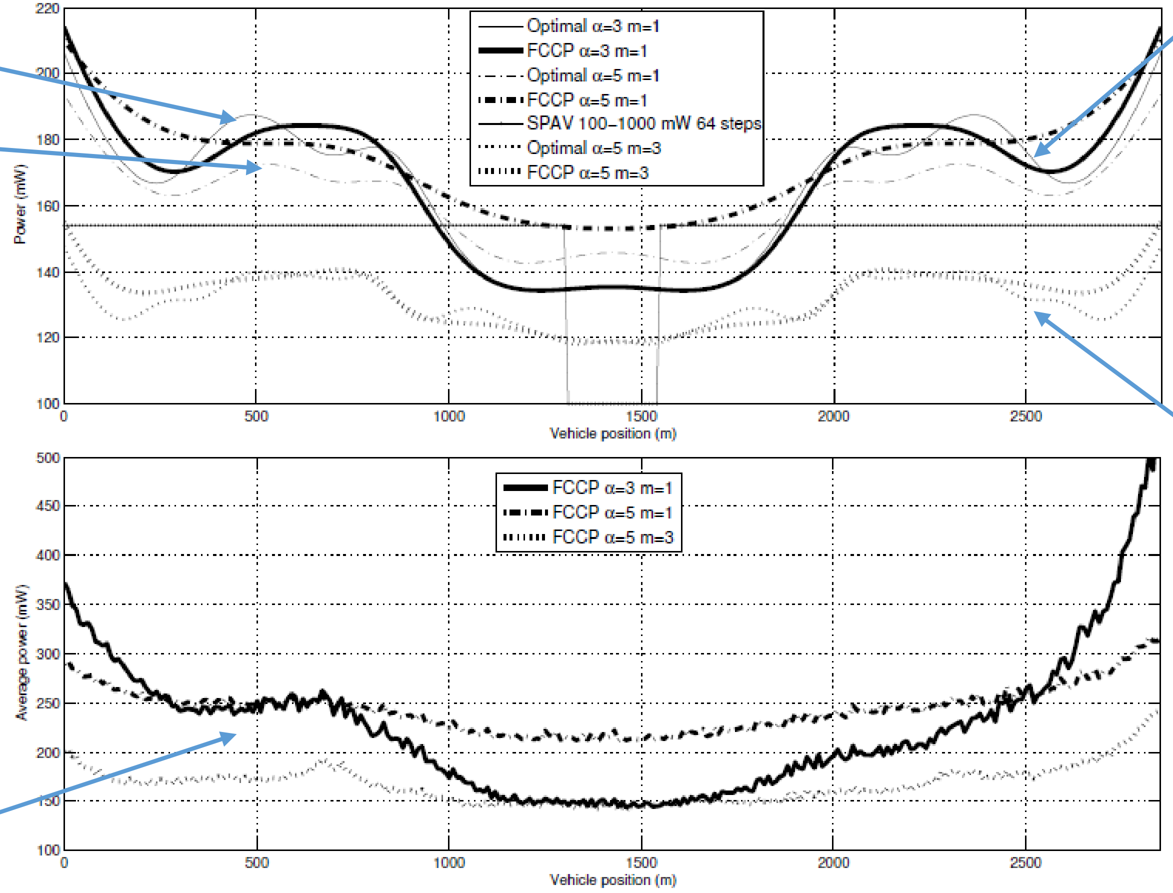
Results: static scenarios equispaced

Fairness α=3

Fairness α=5

As α increases:
- "more" fair: allocation becomes flat
- total power (sum) allocated decreases: less efficiency

Realistic simulation:
- approximately tracks optimal allocation
- Higher average power, why? See CBR next



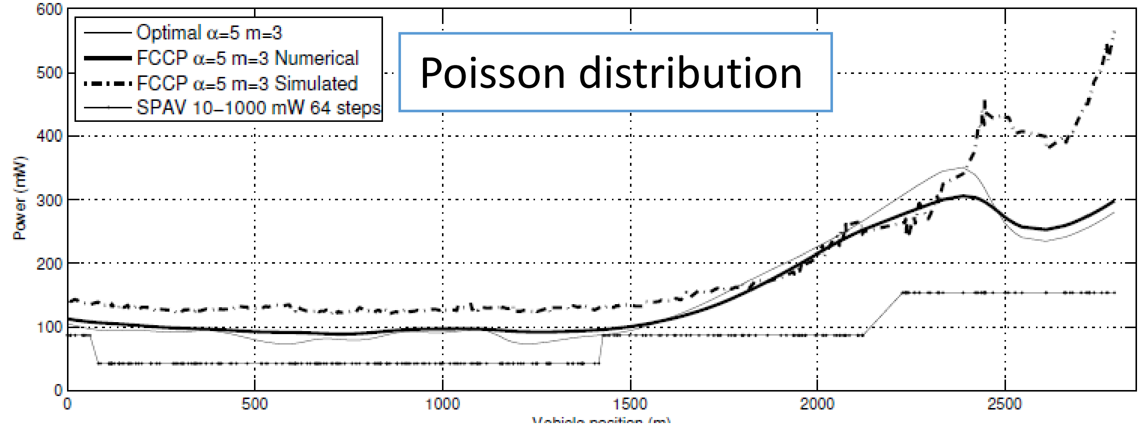
(a) Equispaced vehicles. Fairness notions. Numerical vs simulation. Top: Numerical ideal MAC. Bottom: Realistic simulation.

Rayleigh fading, m=1

More fading (m=1) makes channel less occupied (packets lost due to fading) and so it allows for higher average power

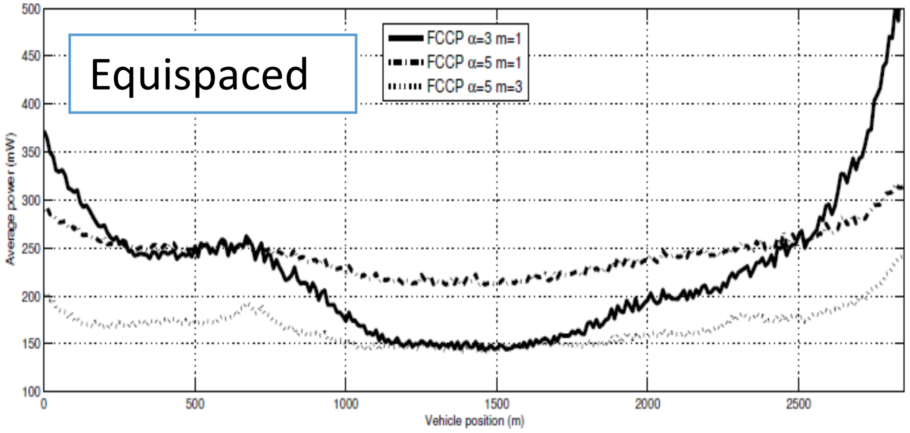
Rician fading, m=3

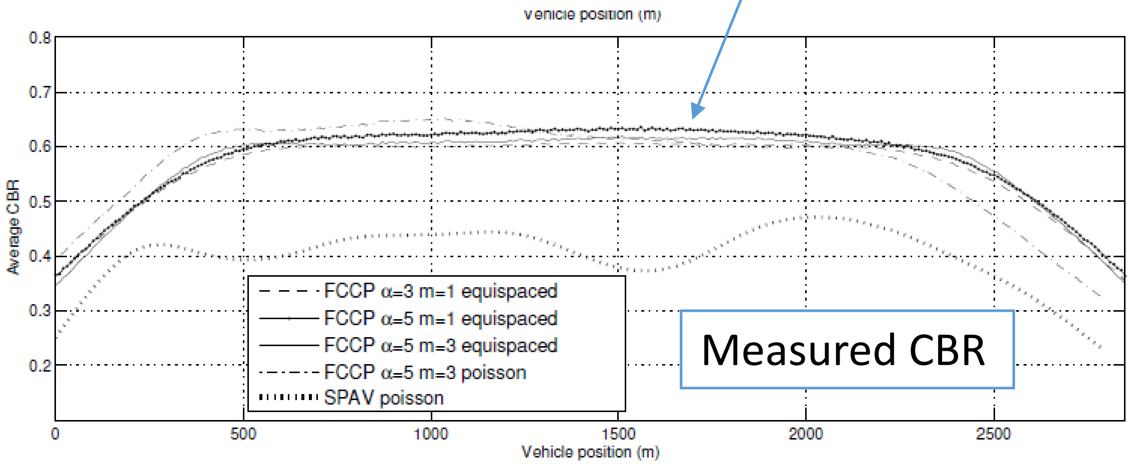
Results: static scenarios and CBR



Measured CBR in the **realistic simulation**:

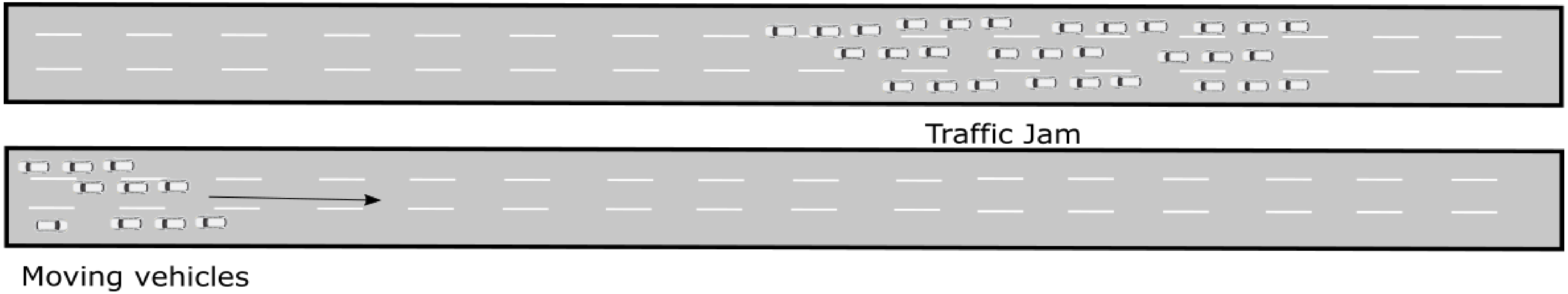
- Since FCCP uses the measured CBR, it **correctly adapts to the actual channel load**
- So the average power is higher because the actual channel load allows it
- **Not necessary to converge** to the optimal value in order **to keep the CBR below MBL**



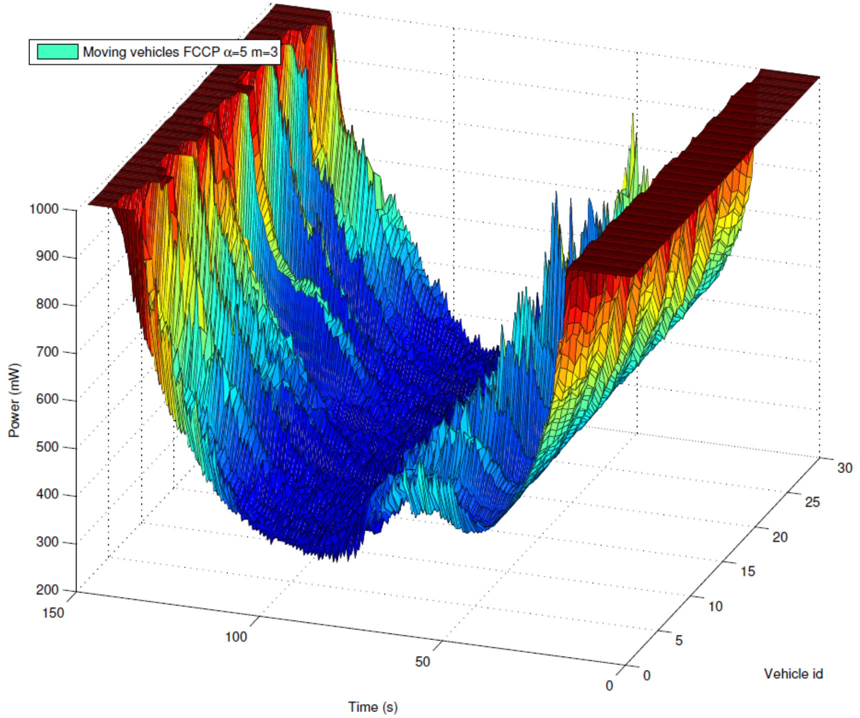


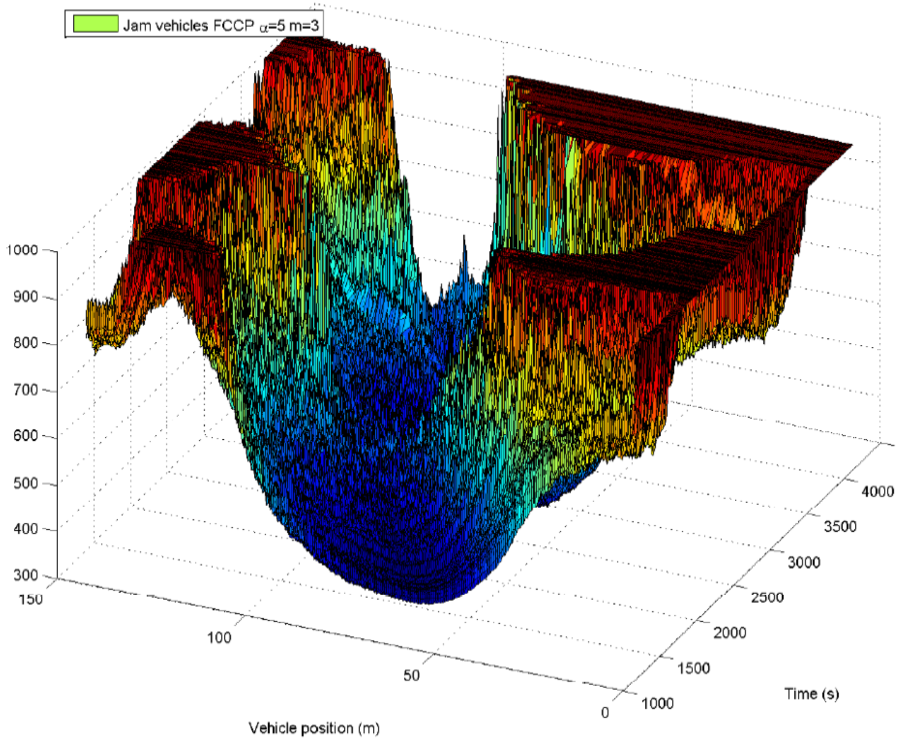
Results: configuration of dynamic scenarios

- **Realistic**: FCCP simulated with OMNET++ with MAC, collisions, capture effect and SINR evaluation
- Cluster of moving vehicles (30) approaches and passes a traffic jam (285 vehicles)
- Moving vehicles:
  - Speed Uniform (26,32) m/s
  - Beaconing rate for moving vehicles proportional to speed between 8.125 and 10 beacons/s
- Traffic jam
  - Beaconing rate Uniform (4,6) beacons/s



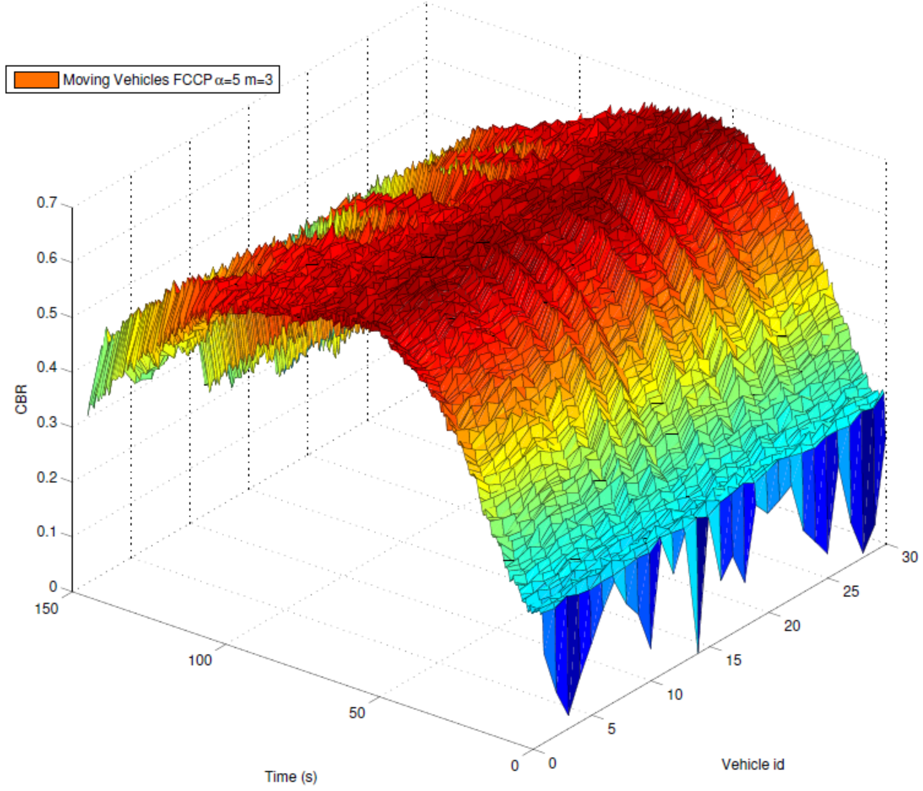
Results: dynamic scenarios

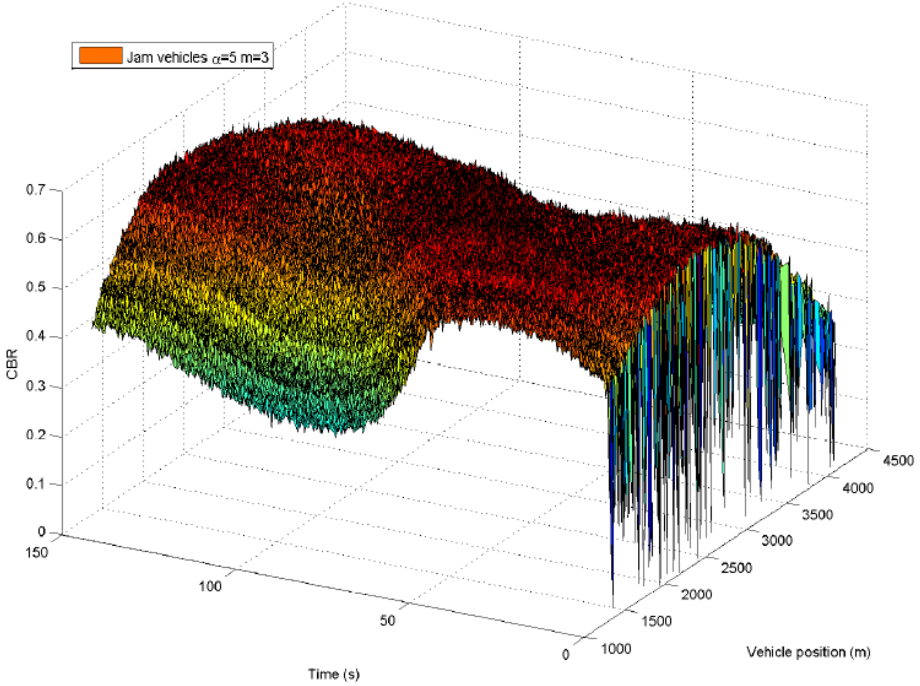




- Vehicles quickly reduce power to adapt to CBR in both cases
- Powers recover the maximum value as son as the congestion is over

Results: dynamic scenarios





- CBR is kept at the MBL threshold except for brief peridos of adaptation

Conclusions and future work

- FCCP, a NUM-based algorithm for DCC:
  - **Maximizes** power
  - Keep the **beaconing load under** a selectable **MBL**
  - **Distributed**
  - **Fair** and allows to **select the fairness notion**
  - Seamlessly **adapt to** environmental **changes**
  - **Dynamically** and **autonomously configurable** to particular vehicle needs
- Future work:
  - Consider SINR in the design
  - **Joint** power-beaconing rate control for DCC

Thanks a lot…

Questions?

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Slides available at http://ait.upct.es/eegea/pub/fccpslides.pdf