Resource Competition in a Highly Networked World of Humans and Things

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Referenced papers by I. Stavrakakis may be downloaded from
http://www.di.uoa.gr/~ioannis/publications.html

Outline

Motivation (environment – early study)

Decision-making in uncoordinated competitive environment - formulation

- **rational case – Price of Anarchy**
- **limited info case**
- **human driven case**
  - **Prospect Thy**
  - **alternative models**
  - **heuristics**

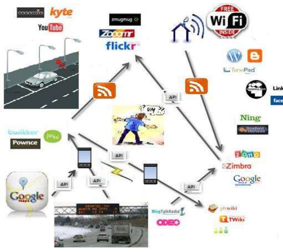
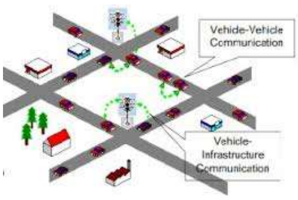
Alternative, partially coordinated approaches

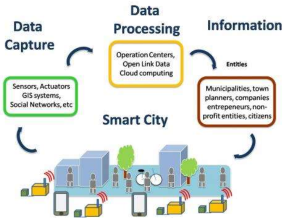
- **Auctioning resources**
- **ICT-supported distributed apps**

Emerging Environment - Motivation

Highly networked world / social networking / smartphone proliferation /exploding IoT

➔ **Rich state information diffused everywhere**



state information ➔ resource (availability) information

Early work in this direction: Enhance parking search by exploiting ICT-enabled information diffusion

Major issues with Non-Assisted (Random) parking search

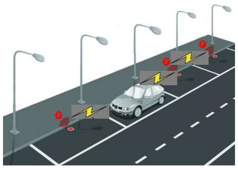
- Traffic congestion problems
- Environmental burden

Annual damage in Schwabin (Munich, Germany)

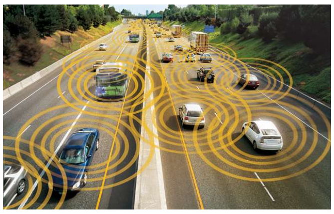
- 3.5 million Euros for gasoline/diesel
- 150.000 hours of waiting time
- ~every second vehicle is in search for parking space

Exploiting diffused information in opportunistically-assisted (OAPS) parking search

- ❑ Parking spots equipped with sensors



- ❑ Vehicles equipped with wireless interfaces / storage / processing capability



- ❑ Inter-vehicle & vehicle-parking spot communication

*E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, "**Opportunistically-assisted parking service discovery: now it helps, now it does not**", Pervasive and Mobile Computing (PMC), Vol. 8, Iss. 2, April 2012.*

Comparative study : OAPS vs NAPS

2 different strategies for locating and occupying parking spots.

A) Opportunistically-assisted parking search (OAPS)

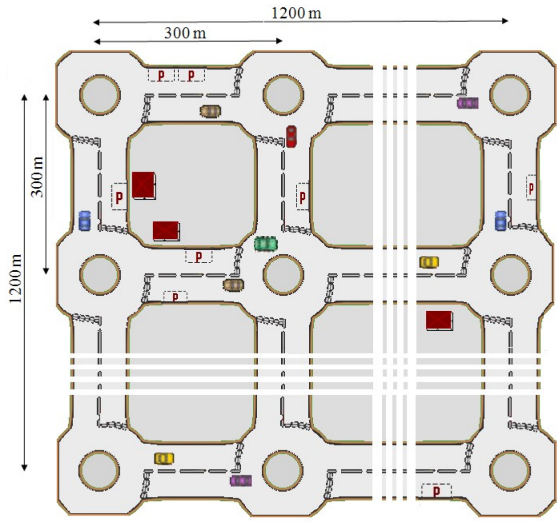
- Inter-vehicle & vehicle-parking spot communication

- Parking spots equipped with sensors
- Vehicles equipped with wireless interfaces, storage, processing
- Information exchanged: (spot location, status, timestamp)

B) Non-assisted parking search (NAPS)

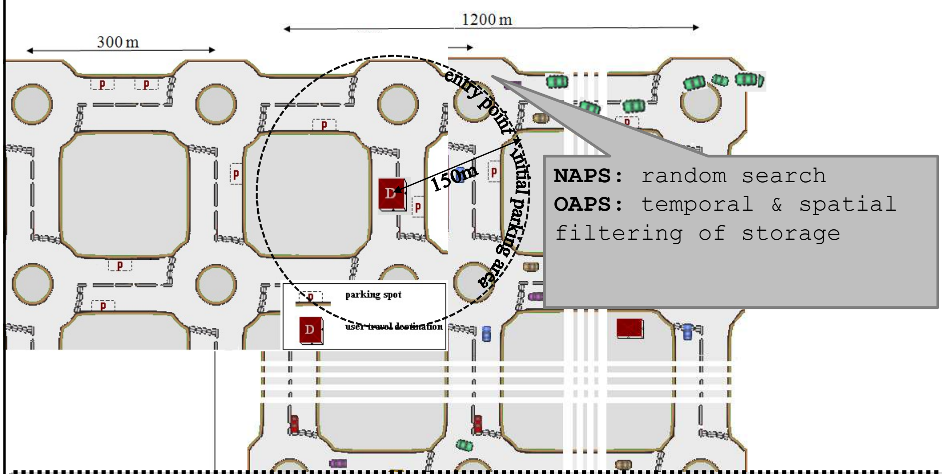
- Random sequential search
- End of search: the first vacant parking spot
- ↑parking search time ⇨ ↑parking search area

Comparative study : OAPS vs NAPS



OAPS vs NAPS

Methodology – vehicle movement



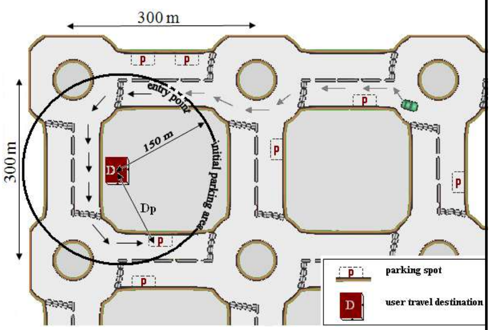
❑ NAPS, OAPS: The radius of the search area grows progressively as parking search time increases.

OAPS vs NAPS

Performance Metrics

(Once the driver enters the initial parking search area…)

1) Parking search time, T_{ps}
2) Parking search route length, R_{ps}
3) Destination-parking spot distance, D_p



NAPS vs OAPS

Simulation results

-- Does the opportunistic system assisted parking discovery always help?? --

Parking search under two scenarios:

a) uniformly distributed destinations

b) concentrated destinations within a particular (hotspot) road.

- information dissemination → synchronizes movement patterns → intensifies competition
  - OAPS worse than NAPS

Lesson Learned

(More) Information may yield worse performance!
(" less is more")

(Competition Increase due to Information dissemination is to blame)

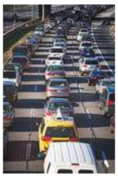
(refer also to another "less is more" case later)

Challenge: Decision-making in the presence of competition

(more) information ➔ easier/better decisions ?

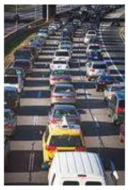
A free spot over there !!!

Go for it!

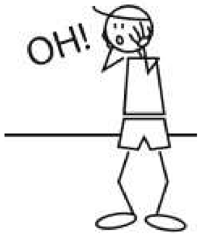


Opps! Go for another one

Opps! Try another one



!?!

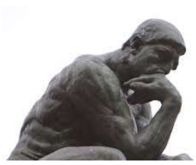


Better if I were not told anything!!!

?

Richer information ➔ easier decisions ?

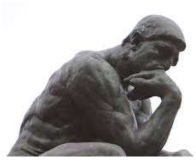
A free spot over there !!!



???

Richer information ➔ easier decisions

A free spot over there !!!



Think wiser !

MAIN FOCUS OF THIS COURSE

**Decision-making (or Resource Selection)
in Distributed, Uncoordinated, Resource-limited, Competitive Environments**

in a Highly Networked World of Humans and Things

Resource Competition for a Common Channel (Resource) by Distributed Users

(… an old problem …)

… to TALK or to NOT TALK?

humans at a cocktail **party**
(shared air, acoustical)

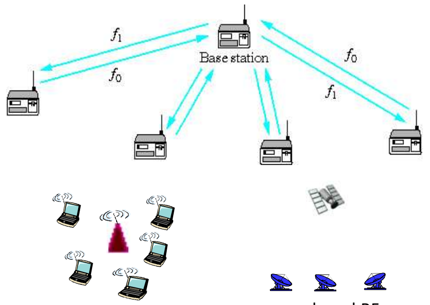
Some Competition Cost

Human-driven competition / Human-driven conflict resolution/avoidance

Resource Competition for a Common Channel (Resource) by Distributed Users

(… an old and … classical networking problem …)

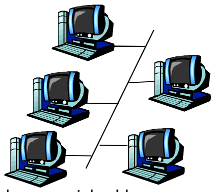
ALOHA



shared RF
(e.g., 802.11 WiFi)

shared RF
(satellite)

ETHERNET



bus: coaxial cable

… to TRANSMIT or to NOT TRANSMIT?

Some Competition Cost

Protocol-driven conflict resolution/avoidance

Resource Competition for a Common Channel (Resource) by Distributed Users

(… a current and growing problem in a highly networked world…)

Common Aspects

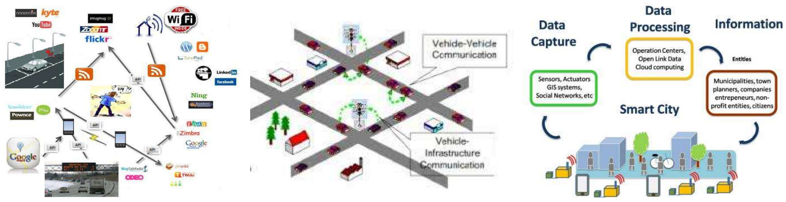
- A common resource (channel)
- Distributed non-communicating users (competitors)
  - random / unknown to others need for the resource
  - aware of the resource availability
- Competition costs
  - collisions / congestion

Resource Competition for a Common Channel (Resource) by Distributed Users

(… a current and growing problem in a highly networked world…)

A common resource (*channel*)

The existence/availability of a ***Wealth of Common (City-Wide) Resources*** can easily become known to potential users



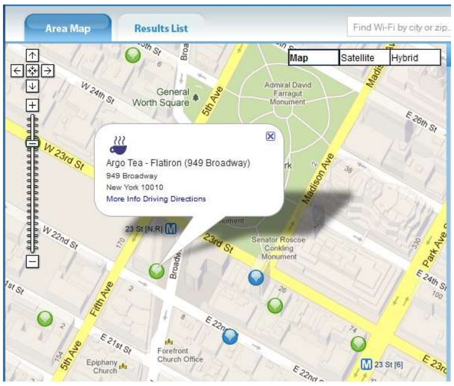
Some resources may be very ***inexpensive (attractive) but limited***
➢ a clear preference over *abundant but expensive alternatives*

competition emerges

Example: Access point association

Cheap but best-effort (public) WLAN

vs. More reliable fee-based wireless access point



Competition reduces quality of service

Example: Route selection

Slower (public) toll-free road

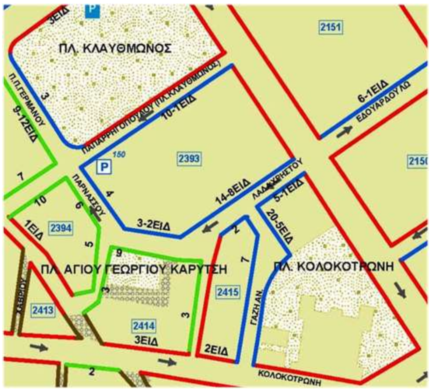
Vs Faster toll road

Competition reduces quality of service

Example: Parking spot selection

Cheap but scarce (public) on-street parking

vs. Expensive but abundant parking lots



Competition reduces quality of service

Part A
Decision-making in Distributed, Uncoordinated, Resource-limited ,Competitive Environments

With **some cost if trying but failing to find a resource** (spot)

Major Question posed

TO COMPETE OR TO NOT COMPETE?

that is the question

- ❑ *to compete for a limited-inexpensive resource or go for the unlimited, expensive alternative?*

  (cost of failure: usage of the expensive resource PLUS paying a failing penalty)

Uncoordinated Resource Selection Problem

N competitors *(*drivers) : autonomous selfish decision-makers

***2* types of parking resources to decide on**

- ***R*** “inexpensive” on-street parking (***osp***) or public spots
  - $c_{osp,s}$: price paid for an osp spot
- “infinite” expensive parking spots in (private) parking lot (***pl***)
  - c_{pl}: price paid for a pl spot [$c_{pl} = \beta\, c_{osp,s}$, $\beta > 1$]

If demand exceeds R, failed attempts pay $c_{osp,f} = \gamma\, c_{osp,s} > \beta\, c_{osp,s}$
(i.e., pay some congestion/failure penalty and then go to the parking lot)

$\delta = \gamma - \beta > 0$ (congestion / lack-of-coordination penalty)

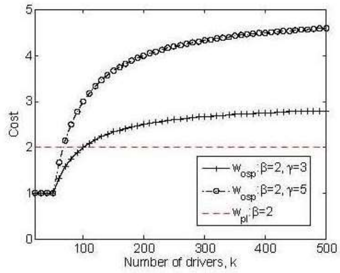
(*) Amount of finite resources ***R*** and costs are known (via ICT technology)

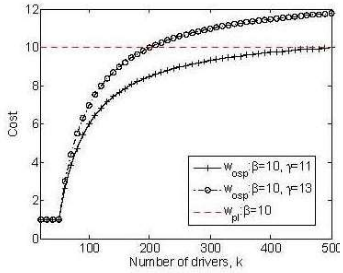
Uncoordinated Resource Selection Problem

- Cost of a player *choosing* PL when k>R compete for OSP: $w_{pl}(k) = c_{pl}$
- Cost of a player *choosing* OSP when k>R compete for OSP:

$$w_{osp}(k) = \min(1, R/k)c_{osp,s} + \left(1 - \min(1, R/k)\right)\gamma c_{osp,s}$$

  - non-decreasing function of demand k
  - users may end up using either an OSP or a PL spot





Cost functions for R=50 and $c_{osp,s}$ =1

How are decisions to compete or not to compete are taken?

The full rationality vs. bounded rationality question

Assumptions affecting how selections / decisions are made:

- Perfect *vs.* imperfect **information/knowledge** on number of competitors
- Full or limited **computational capacity** of decision-maker to assess the impact of choices
- Cognitive **biases** of decision-maker

Uncoordinated Resource Selection problem formulation under:

- ❑ **Full Rationality: perfect knowledge, unlimited computational capacity**
- ❑ **Bounded Rationality:**
  - ➢ **Limited / imperfect information**
  - ➢ **Limited computational capacity and cognitive biases (human-driven)**
    - **inputs from behavioral economics, cognitive psychology, etc**
    - **models for bounded rationality and assessment of its impact**

Part A
Decision-making in Distributed, Uncoordinated, Resource-limited ,Competitive Environments

CASE A-1
(classical) Expected Utility Maximization Framework

- ❑ **Full Rationality: perfect knowledge, unlimited computational capacity**
- ❑ **Bounded Rationality:**
  - ➢ **Limited / imperfect information**

*E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, "**Leveraging information in parking assistance systems**", IEEE Transactions on Vehicular Technology, 62, 4309–4317, 2013.*

Uncoordinated Resource Selection Problem: The parking spot selection game

Drivers = strategic players

- Amount of finite resources ***R*** and prices/costs are known (via ICT technology)
- **unbounded / bounded rationality wrt parking demand (# of competitors)**

Complete knowledge of the parking demand	**Strategic game** (A)	
Probabilistic knowledge	**Bayesian game** (B)	Methodology ➢ **Equilibrium states** ➢ **Optimal outcomes** ➢ **Comparison via Price of Anarchy**
Strictly incomplete knowledge	**Pre Bayesian game** (pB)	

The (strategic) parking spot selection game Γ(N)

- N drivers / players
- ***R*** on-street-parking – ***osp*** (public) + Infinite parking lot – ***pl*** (private) spots

- Action set: {***osp*** (public) , ***pl*** (private) }
- Action of player i : α_i
- Actions of all players except player i: α_{-i}
- Action profile $\alpha=(\alpha_i , \alpha_{-i})$ ➔ 2**N of them

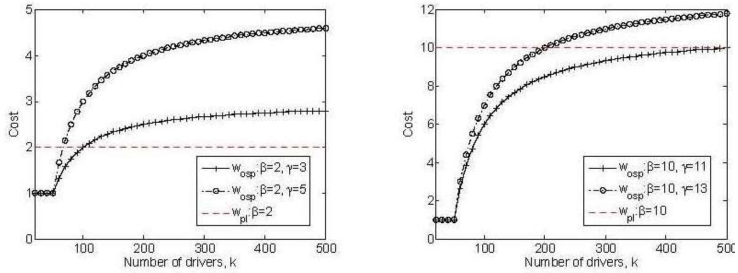
- Action meta-profile α(m): any profile with m players competing
  ➔ N+1 meta-profiles

RECALL: Cost for choosing action PL or OSP

- Cost of a player *choosing* PL when k>R compete for OSP: $w_{pl}(k) = c_{pl}$
- Cost of a player *choosing* OSP when k>R compete for OSP:

$$w_{osp}(k) = \min(1, R/k)c_{osp,s} + \left(1 - \min(1, R/k)\right)\gamma c_{osp,s}$$

  - non-decreasing function of demand k
  - Users may end up using either an OSP or a PL spot



Cost functions for R=50 and $c_{osp,s}$ =1

The (strategic) parking spot selection game

Expected **cost for player *i*** under action profile $\alpha=(\alpha_i, \alpha_{-i})$

$$c_i^N(a_i, a_{-i}) = \begin{cases} w_{osp}(N_{osp}(a)), & \text{for } a_i = osp \\ w_{pl}(N - N_{osp}(a)), & \text{for } a_i = pl \end{cases}$$ ($= c_{pl}$, fixed)

- ***Nash Equilibrium state:***
  a situation in which no player can decrease its cost (increase its utility) by changing his strategy unilaterally

  Every symmetric game with two strategies has an equilibrium in pure strategies
  - Cheng, S.G. et al.: Notes on the equilibria in symmetric games, Proc. 6th Workshop On Game Theoretic And Decision Theoretic Agents (collocated with IEEE AAMAS). New York, USA (2004)

Derivation of pure equilibrium states/strategies

- The action profile $\alpha=(\alpha_i, \alpha_{-i})$ is a pure Nash equilibrium if for all *i*∈*N*

$$a_i \in \arg\min_{a'_i \in A_i} (c_i^N(a'_i, a_{-i}))$$

- How to find EQ:

  Identify the conditions on the number of competing agents that break the equilibrium definition and reverse them.

  A driver is motivated to change his action in the following circumstances

$$when\ a_i = pl \text{ and } w_{osp}(N_{osp}(a)+1) < c_{pl} \qquad \textbf{(*)}$$

$$when\ a_i = osp \text{ and } w_{osp}(N_{osp}(a)) > c_{pl} \qquad \textbf{(**)}$$

Derivation of pure equilibrium states/strategies

<u>*Lemma*</u>: a player is motivated to change his action α_i as follows

- $a_i = \text{pl}$ and (a) $N_{\text{osp}}(a) < R \leq N$ or

  (b) $R \leq N_{\text{osp}}(a) < N_0 - 1 \leq N$ or

  (c) $N_{\text{osp}}(a) < N \leq R$
- $a_i = \text{osp}$ and $R < N_0 < N_{\text{osp}}(a) \leq N$

where $N_0 = R(\gamma - 1)/\delta \in \mathbb{R}$.

<u>*Hint*</u>: for (b), require that (*) holds and for the second bullet require that (**) holds and get the condition on $N_{osp}(\alpha)$

Pure equilibrium strategies

The strategic parking spot selection game has the following EQ profiles

a) for $N \leq N_0$, a unique NE profile a^* with $N_{\text{osp}}(a^*) = N_{\text{osp}}^{\text{NE},1} = N$;

b.1) for $N > N_0$ and $N_0 \in (R, N) \setminus \mathbb{N}^*$, $\binom{N}{\lfloor N_0 \rfloor}$ NE profiles a' with $N_{\text{osp}}(a') = N_{\text{osp}}^{\text{NE},2} = \lfloor N_0 \rfloor$;

b.2) for $N > N_0$ and $N_0 \in [R+1, N] \cap \mathbb{N}^*$, $\binom{N}{N_0}$ NE profiles a' with $N_{\text{osp}}(a') = N_{\text{osp}}^{\text{NE},2} = N_0$ and $\binom{N}{N_0-1}$ NE profiles $a^\star$ with $N_{\text{osp}}(a^\star) = N_{\text{osp}}^{\text{NE},3} = N_0 - 1$.

# drivers, N	#competing drivers for OSP (public) parking under NE
$\leq \frac{R(\gamma-1)}{\delta}$	N
$> \frac{R(\gamma-1)}{\delta}$	$\frac{R(\gamma-1)}{\delta}$

Efficiency of pure equilibrium states/strategies

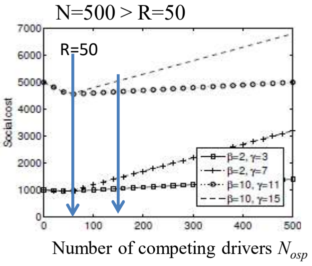
Efficiency Metric**: **The Price of Anarchy (PoA ≥ 1)**

= [social cost under EQ state] / [optimal social cost]

Social cost under action profile α:

$$C(N_{osp}(a)) = \sum_{i=1}^{N} c_i^N(a) = \begin{cases} c_{osp,s}(N\beta - N_{osp}(a)(\beta-1)), & \text{if } N_{osp}(a) \leq R \\ c_{osp,s}(N_{osp}(a)\delta - R(\gamma-1) + \beta N), & \text{if } R < N_{osp}(a) \leq N \end{cases}$$

Use under a* : if N ≤ N_0 use $N_{osp}(\alpha^*)$ = N ; if N ≥ N_0 use $N_{osp}(\alpha^*)$= $N_{\text{osp}}^{\text{NE},2} = \lfloor N_0 \rfloor$

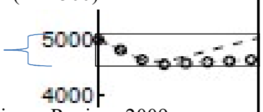


cost minimized at $N_{osp} = R =$ ***50***

Social cost increases as N_{osp} moves away from R (lack of coordination penalty)

Cost at EQ: $N_{osp} = N_{\text{osp}}^{\text{NE},2} = \lfloor N_0 \rfloor = \lfloor R(\gamma-1)/\delta \rfloor$
$=R*(15-1)/(15-10) = R*2.8=$***140*** (<N=500)

lack of coordination penalty of 500



** E. Koutsoupias, C. H. Papadimitriou, “Worst-case equilibria”, Computer Science Review, 2009.

Efficiency of pure equilibrium states/strategies

Optimal social cost: (exactly min{R,N} players compete – no fail and all osp spots used)

$$C_{opt} = \sum_{i=1}^{N} c_i^N(a_{opt}) = c_{osp,s}[min(N,R) + \beta \cdot max(0, N-R)]$$

Price of Anarchy

$$\text{PoA} = \begin{cases} \frac{\gamma N-(\gamma-1)\min(N,R)}{\min(N,R)+\beta\max(0,N-R)}, & if\ N_0 \geq N \\ \frac{\lfloor N_0 \rfloor \delta - R(\gamma-1)+\beta N}{R+\beta(N-R)}, & if\ N_0 < N \end{cases}$$

= 5000 / 4500 = 1.11

PoA ≤ 1 / [1-R/N] , for N>R

Efficiency of pure equilibrium states/strategies

Price of Anarchy

$$\text{PoA} = \begin{cases} \frac{\gamma N-(\gamma-1)\min(N,R)}{\min(N,R)+\beta\max(0,N-R)}, & if\ N_0 \geq N \\ \frac{\lfloor N_0 \rfloor \delta - R(\gamma-1)+\beta N}{R+\beta(N-R)}, & if\ N_0 < N \end{cases}$$

Varying N **or** R: For $N \leq N_0$ or, equivalently, for $R \geq \frac{N\delta}{\gamma-1}$, it holds that $\frac{\vartheta PoA}{\vartheta N} > 0$ and $\frac{\vartheta PoA}{\vartheta R} < 0$. Therefore, the PoA is strictly increasing in N and decreasing in R. On the contrary, for $N > N_0$ or $R < \frac{N\delta}{\gamma-1}$, the PoA is strictly decreasing in N and increasing in R, since $\frac{\vartheta PoA}{\vartheta N} < 0$ and $\frac{\vartheta PoA}{\vartheta R} > 0$.

Varying δ: For $N \leq N_0$ or, equivalently, for $\delta \leq \frac{R(\beta-1)}{N-R}$, it holds that $\frac{\vartheta PoA}{\vartheta \delta} > 0$. Therefore, the PoA is strictly increasing in δ. For $\delta > \frac{R(\beta-1)}{N-R}$, we get $\frac{\vartheta PoA}{\vartheta \delta} = 0$. Hence, if δ exceeds $\frac{R(\beta-1)}{N-R}$, PoA is insensitive to changes of the excess cost δ.

Varying β: For $N \leq N_0$ or, equivalently, for $\beta \geq \frac{\delta(N-R)+R}{R}$, it holds that $\frac{\vartheta PoA}{\vartheta \beta} < 0$ and therefore, the PoA is strictly decreasing in β. On the contrary, for $\beta < \frac{\delta(N-R)+R}{R}$, the PoA is strictly increasing in β, since $\frac{\vartheta PoA}{\vartheta \beta} > 0$.

Efficiency of pure equilibrium states/strategies

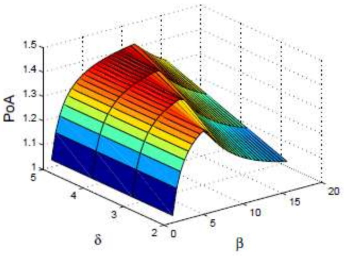
Optimal social cost, Copt
$c_{osp,s}[\min(N,R)+\beta\max(0,N-R)]$

↑ R competing drivers

# drivers, N	Social cost in EQ, Ceq	
$\leq \frac{R(\gamma-1)}{\delta}$	$c_{osp,s}[N\gamma-\min(N,R)(\gamma-1)]$	N compete
$> \frac{R(\gamma-1)}{\delta}$	$c_{osp,s}\beta N$	R(γ-1)/δ compete

PoA>1 : due to competition and paying the (lack-of-coordination) cruising cost

Pricing (β) and failure cost/ overhead (δ) shaping guidelines



$N=500, R=160, c_{osp,s}=1€$

β	δ	PoA➔ 1
$\geq \frac{\delta(N-R)+R}{R}$	>0	↑β
$< \frac{\delta(N-R)+R}{R}$	>0	↓β
>1	$\leq \frac{R(\beta-1)}{N-R}$	↓δ

The (strategic) mixed-action selection game

Practical strategies for real systems / a mixed action $p = (p_{osp}, p_{pl})$

Expected cost for player choosing *osp* or *pl*, respectively, when all N-1 play according to the mixed-action p

$$c_i^N(osp,p) = \sum_{N_{osp}=0}^{N-1} w_{osp}(N_{osp}+1)B(N_{osp}; N-1, p_{osp})$$

$$c_i^N(pl,p) = c_{pl}$$

Expected cost for symmetric profile (all play according to the mixed-action p)

$$c_i^N(p,p) = p_{osp}\cdot c_i^N(osp,p) + p_{pl}\cdot c_i^N(pl,p)$$

The (strategic) mixed-action selection game

- ***Existence of Mixed-action Nash Equilibrium:***

  Every symmetric game with more than two players and increasing cost functions (of the number of players) has a unique mixed-action equilibrium
  - Ashlagi, I., Monderer, D., Tennenholtz, M.: Resource selection games with unknown number of players. In: Proc. AAMAS ’06. Hakodate, Japan (2006)

- ***The Mixed-action Nash Equilibrium state:***

  The strategic parking spot selection game has a unique mixed-action NE

$$p^{\mathrm{NE}} = (p^{\mathrm{NE}}_{\mathrm{osp}}, p^{\mathrm{NE}}_{\mathrm{pl}}),$$ where $p^{\mathrm{NE}}_{\mathrm{osp}} = 1$ if $N \leq N_0$ and $p^{\mathrm{NE}}_{\mathrm{osp}} = N_0/N$ if $N > N_0$, with $p^{\mathrm{NE}}_{\mathrm{osp}} + p^{\mathrm{NE}}_{\mathrm{pl}} = 1$ and $N_0 \in \mathbb{R}$.

Sketch of proof: Set the requirement to be fulfilled by the profiles at EQ:

$$c_i^N(osp, p^{NE}) = c_i^N(pl, p^{NE})$$

Equilibrium states/strategies (pure / mixed-action strategies

- Pure NE

# drivers, N	#competing drivers for public parking space
$\leq \frac{R(\gamma-1)}{\delta}$	N
$> \frac{R(\gamma-1)}{\delta}$	$\frac{R(\gamma-1)}{\delta}$

- Symmetric mixed-action NE

# drivers, N	Probability of competing for public parking space
$\leq \frac{R(\gamma-1)}{\delta}$	1
$> \frac{R(\gamma-1)}{\delta}$	$\frac{R(\gamma-1)}{\delta N}$

Decision-making under knowledge constraints (a type of bounded rationality)

- The **Bayesian model: probabilistic information**
  - Drivers know
    a) probability for a driver to be active (interested in parking)
    b) total number of drivers
- The **pre Bayesian model: strictly incomplete information**
  - Drivers know their total number (***upper bound on competitors***)

A Bayesian parking spot selection game

- $A_i = \{osp, pl, \oslash\}$ *is the set of potential actions for each driver* $i \in \mathcal{N}$;
- $\Theta_i = \{0, 1\}$ *is the set of types for each driver* $i \in \mathcal{N}$, *where* 1 (0) *stands for active (inactive) drivers;*
- $S_i : \Theta_i \to A_i$ *is the set of possible strategies for each driver* $i \in \mathcal{N}$;
- $c_i^{N_B}(s(\vartheta), \vartheta)$ *is the cost functions for each driver* $i \in \mathcal{N}$, *for every type profile* $\vartheta \in \times_{k=1}^{N} \Theta_k$ *and strategy profile* $s(\vartheta) \in \times_{k=1}^{N} S_k$, *that are functions of* $w_{osp}(\cdot)$ *and* $w_{pl}(\cdot)$, *as defined for* $\Gamma(N)$, *and also written as* $c_i^{N_B}(s(\vartheta), \vartheta) = c_i^{N_B}(s_i(\vartheta_i), s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})$;
- p_{act} *is the probability for a driver to be active.*

A Bayesian parking spot selection game

Equilibria:

For the game $\Gamma_B(N)$, the strategy profile $s' \in \times_{k=1}^{N} S_k(\vartheta_k = 1)$ is a Bayesian NE if, for all $i \in \mathcal{N}$ with $\vartheta_i = 1$

$$s_i(\vartheta_i) \in \arg\min_{s_i' \in S_i} (c_i^{N_B}(s_i(\vartheta_i), s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})) \quad \text{or,}$$

$$s_i(\vartheta_i) \in \arg\min_{s_i' \in S_i} \sum_{\vartheta_{-i}} f_\Theta(\vartheta_{-i}/\vartheta_i) c_i^{\sum_k \vartheta_k}(s_i', s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})$$

Derivation approach

$$c_i^{N_B}(pl, p) = c_{pl} \qquad c_i^{N_B}(osp, p) = \sum_{n_{act}=0}^{N-1} c_i^{n_{act}+1}(osp, p) B(n_{act}; N-1, p_{act})$$

Equilibria:

The Bayesian parking spot selection game $\Gamma_B(N)$ has unique symmetric equilibrium profiles $p^{NE_B} = (p_{osp}^{NE_B}, p_{pl}^{NE_B})$, with $p_{osp}^{NE_B} + p_{pl}^{NE_B} = 1$. More specifically:

- a unique pure (Bayesian Nash) equilibrium with $p_{osp}^{NE_B} = 1$, if $p_{act} < \frac{N_0}{N}$,
- a unique symmetric mixed-action Bayesian Nash equilibrium with $p_{osp}^{NE_B} = \frac{N_0}{N p_{act}}$, if $p_{act} \geq \min(\frac{N_0}{N}, 1)$,

where $N_0 \in \mathbb{R}$.

Equilibrium states under Bayesian Game

- Symmetric mixed-action Bayesian Nash equilibria

Activation probability, p_{act}	(symmetric) Probability of competing
$< \frac{R(\gamma-1)}{\delta N}$	1
$\geq \min\left(\frac{R(\gamma-1)}{\delta N}, 1\right)$	$\frac{R(\gamma-1)}{\delta N p_{act}}$

Equilibrium states under strict uncertainty

Knowledge of an upper bound on demand, N

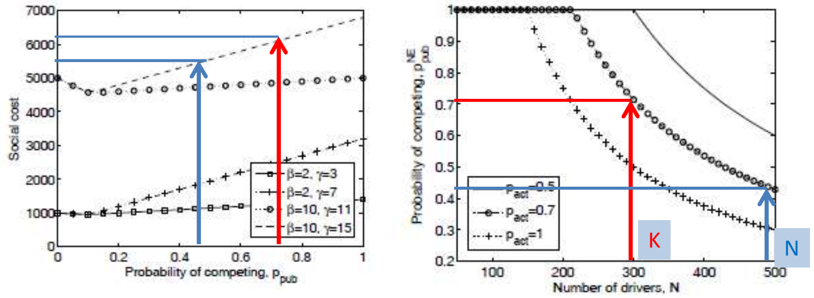
For **the pre-Bayesian parking spot selection game** it holds that

Symmetric mixed-action *safety-level equilibrium* (playing to min worst cost)

↕

Symmetric mixed-action equilibrium of the strategic game Γ(N) with N players

Less-is-more phenomena under strictly incomplete knowledge of parking demand



- Social cost increases with the probability of competing
- Probability of competing (in EQ states), decreases with N

↓

- If N is maximum number of drivers and K(<N) is real number of active drivers (interested in parking) , then in the safety-level equilibrium,

$$p_{pub,N} < p_{pub,K} \rightarrow \text{social\_cost}_N < \text{social\_cost}_K$$

(provided the average number of drivers that compete for public space is still over R)

EQ strategies for Strategic, Bayesian and pre-Bayesian Resource Selection Game

TABLE I
EQUILIBRIUM STRATEGIES FOR THE STRATEGIC, BAYESIAN AND PRE-BAYESIAN PARKING SPOT SELECTION GAME

strategic Parking Spot Selection Game, $\Gamma(N)$		
Condition	Equilibrium type	Equilibrium expression
$N \leq N_0,\ N_0 \in \mathbb{R}$	pure Nash Eq	$N_{osp}^{NE} = N$
$N > N_0,\ N_0 \in (R, N)\backslash\mathbb{N}^*$	pure Nash Eq	$N_{osp}^{NE} = \lfloor N_0 \rfloor$
$N > N_0,\ N_0 \in [R+1, N] \cap \mathbb{N}^*$	pure Nash Eq	$N_{osp}^{NE} = N_0,\ N_{osp}^{NE} = N_0 - 1$
$N > N_0,\ N_0 \in \mathbb{R}$	mixed-action Nash Eq	$p_{osp}^{NE} = \frac{N_0}{N}$
Bayesian Parking Spot Selection Game, $\Gamma_B(N)$		
Condition	Equilibrium type	Equilibrium expression
$p_{act} < \frac{N_0}{N},\ N_0 \in \mathbb{R}$	pure Bayesian Nash Eq	$p_{osp}^{NE_B} = 1$
$p_{act} \geq \min(\frac{N_0}{N}, 1),\ N_0 \in \mathbb{R}$	mixed-action Bayesian Nash Eq	$p_{osp}^{NE_B} = \frac{N_0}{N p_{act}}$
pre-Bayesian Parking Spot Selection Game, $\Gamma_{pB}(N)$		
Condition	Equilibrium type	Equilibrium expression
$N \leq N_0,\ N_0 \in \mathbb{R}$	pure safety-level Eq	$p_{osp}^{NE_{pB}} = 1$
$N > N_0,\ N_0 \in \mathbb{R}$	mixed-action safety-level Eq	$p_{osp}^{NE_{pB}} = \frac{N_0}{N}$

Part A
Decision-making in Distributed, Uncoordinated, Resource-limited ,Competitive Environments

CASE A-2
Departure from
Full Rationality / Expected Utility Maximization Framework

- **Bounded Rationality:**
  - **Limited computational capacity and cognitive biases (human-driven)**
    - **inputs from behavioral economics, cognitive psychology, etc**
    - **models for bounded rationality and assessment of its impact**

*E. Kokolaki, M. Karaliopoulos, I Stavrakakis, "**On the human-driven decision-making process in competitive environments**", Internet Science Conference, April 10-11, 2013, Brussels*

RECALL: Decisions under Full Rationality

Expected Utility Theory framework

- **Strategic agents** with perfect information, without behavioral biases, aiming at maximizing own welfare
  - –quantified by the expected gain/cost of their actions through EUT framework

- **Expected Utility Theory (EUT) framework**
  - –Expected utility of a lottery equals the sum of the utilities of the lottery outcomes, $U(x_i)$, times their probabilities of the outcomes, $p(x_i)$

$$EU = \sum_{x_i} p(x_i)U(x_i), \quad x_i : \text{choice / alternativ e.}$$

- **Nash equilibrium**
  - –captures best response in terms of expected utility maximization

Deviations from Full Rationality

- ❑ **(Cumulative) Prospect Theory**
  - maintains most of the concepts/assumptions of EUT
  - manipulates both utility measures and prob. to account for biases against risk

- ❑ **Alternative decision-making models & Equilibrium (EQ) concepts (Quantal Response, Rosenthal)**
  - Use probabilistic choice models to capture any unobserved and omitted elements, estimation/computational errors, individual's mood, perceptual variations or cognitive biases
  - In line with the fact that individuals are more likely to make better choices than worse choices, but do not necessarily make the very best choice

- ❑ **Heuristics**
  - ❑ Fast and frugal reasoning solutions / decisions
  - ❑ Emphasis on cognitive processes underlying decisions

Prospect Theory motivation (1)

In several choice problems, individuals' preferences systematically violate EUT !!!

Allais' paradox (indication that people assess utilities and probabilities of outcomes differently from what full rationality/ EUT predicts => contradictions under EUT formulation)

PROBLEM 1: Choose between

A:	2,500 with probability	.33,	B:	2,400 with certainty
	2,400 with probability	.66,		
	0 with probability	.01;		
$N = 72$	[18]			[82]*

Percentage of responses

$EUT_{prospectB} > EUT_{prospectA}$ ⇔ u(2400)>.33u(2500)+.66u(2400)⇔ **.34u(2400) > .33u(2500)**

PROBLEM 2: Choose between

C:	2,500 with probability	.33,	D:	2,400 with probability	.34,
	0 with probability	.67;		0 with probability	.66.
$N = 72$	[83]*			[17]	

$EUT_{prospectC} > EUT_{prospectD}$ ⇔ **.33u(2500) > .34u(2400)**

Prospect Theory motivation (2)

Four-fold pattern of risk attitude: (again, violation of ETU framework)

- High probabilities: risk aversion for gains & risk seeking for losses
- Low probabilities: risk seeking for gains & risk aversion for losses

TABLE I

PREFERENCES BETWEEN POSITIVE AND NEGATIVE PROSPECTS

	Positive prospects				Negative prospects		
Problem 3: $N = 95$	(4,000, .80) [20]	<	(3,000). [80]*	Problem 3′: $N = 95$	(−4,000, .80) [92]*	>	(−3,000). [8]
Problem 4: $N = 95$	(4,000, .20) [65]*	>	(3,000, .25). [35]	Problem 4′: $N = 95$	(−4,000, .20) [42]	<	(−3,000, .25). [58]
Problem 7: $N = 66$	(3,000, .90) [86]*	>	(6,000, .45). [14]	Problem 7′: $N = 66$	(−3,000, .90) [8]	<	(−6,000, .45). [92]*
Problem 8: $N = 66$	(3,000, .002) [27]	<	(6,000, .001). [73]*	Problem 8′: $N = 66$	(−3,000, .002) [70]*	>	(−6,000, .001). [30]

Prospect Theory formulation

Defines prospects (Kahneman & Tversky, 1979):

$$\text{Prospect}: (x_1, p_1; x_2, p_2; \ldots; x_n, p_n)$$

Desirability of a prospect is quantified through generalization of the utility functions and their weighting through *weighting functions* $\pi(p_i)$

$$U = \sum_{i=1}^{n} \pi(p_i) v(x_i)$$

- Decision maker is still a utility maximizer

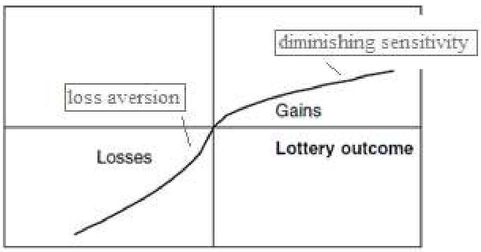
The Prospect Theory (PT) model (Kahneman & Tversky, 1979)

Diminishing sensitivity:

- Impact of a chance diminishes with distance from Reference Point
  (a gain from reference 50 to 100 is less valuable than from 0 to 50)
  (people are more sensitive to extreme outcomes and less to intermediate ones)

Loss aversion:

- Curve is steeper for losses than for gains
  (a high loss hurts more than a high pleasure)



A Hypothetical Value Function

The Cumulative PT (CPT) model (Tversky & Kahneman, 1992)

$$\text{Prospect}: (x_1, p_1; x_2, p_2; \ldots; x_n, p_n)$$

CPT fixes some (experimentally observed) inconsistencies of PT

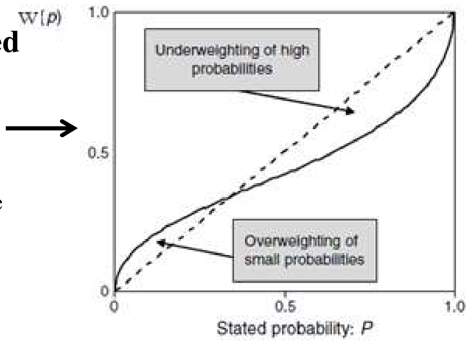
Modifies the probability weighting functions

- PT : transforms probabilities of separate outcomes
- CPT: transforms probabilities of {an outcome or anything better (or worse) than that}

Desirability of a prospect quantified through generalizing:

A. **Outcome probabilities $\{p_i\}$ via decision weights $\{w(p_i)\}$** →
   (diminishing sensitivity: more sensitive around 0 and 1, and less in the middle)

B. Outcome values $\{x_i\}$ via utility functions $\{U(x_i)\}$



The Cumulative PT (CPT) model (Tversky & Kahneman, 1992)

Desirability of a prospect quantified through generalizing:

A. Outcome probabilities $\{p_i\}$ via decision weights $\{w(p_i)\}$

B. **Outcome values $\{x_i\}$ via utility functions $\{U(x_i)\}$**

CPT value of the prospect $(x_1, p_1; \ldots; x_n, p_n)$:

$$U = \sum_{i=1}^{k} \pi_i^- v(x_i) + \sum_{i=k+1}^{n} \pi_i^+ v(x_i), \qquad x_1 \leqslant \ldots \leqslant x_k \leqslant 0 \leqslant x_{k+1} \leqslant \ldots \leqslant x_n.$$

where the decision weights (i.e. the numbers π_i^-, π_i^+) are defined by:

$$\pi_1^- = w^-(p_1), \qquad \pi_i^- = w^-(p_1 + \cdots + p_i) - w^-(p_1 + \cdots + p_{i-1}) \qquad 2 \leqslant i \leqslant k$$

$$\pi_n^+ = w^+(p_n), \qquad \pi_i^+ = w^+(p_i + \cdots + p_n) - w^+(p_{i+1} + \cdots + p_n) \qquad k+1 \leqslant i \leqslant n-1$$

$$v(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\lambda(-x)^\beta & \text{if } x < 0. \end{cases} \quad w^+(p) = p^\gamma / [p^\gamma + (1-p)^\gamma]^{1/\gamma} \quad w^-(p) = p^\delta / [p^\delta + (1-p)^\delta]^{1/\delta}. \quad w^+(0) = w^-(0) = 0, \; w^+(1) = w^-(1) = 1.$$

The values that best fit the experimental results of Kahneman & Tversky are: $\{\alpha = \beta = 0.88;\ \lambda = 2.25;\ \gamma = 0.61;\ \delta = 0.69$

Equilibrium concepts over Cumulative Prospect Thy

- **Nash Equilibrium state**: no player can increase his/her utility (*expected utility value*) by changing his/her strategy unilaterally
  - Mixed-action profiles:
    - *EU value of strategy 1 = EU value of strategy 2*

- **CPT Equilibrium state**: no player can increase his/her utility (*cumulative prospect value*) by changing his/her strategy unilaterally
  - Mixed-action profiles:
    - *CPT value of prospect 1 = CPT value of prospect 2*

Applying CPT to Resource Selection Problem

Two alternatives/prospects: ***l*** (limited resource, osp) and ***u*** (unlimited resource, pl)

CPT value for prospects ***l*** and, ***u*** respectively:

$$CPT_l = \sum_{n=1}^{N} \pi_n^- u(g_l(n)) \qquad CPT_u = u(c_u)$$

With the cost of selecting prospect l when k others do the same given by

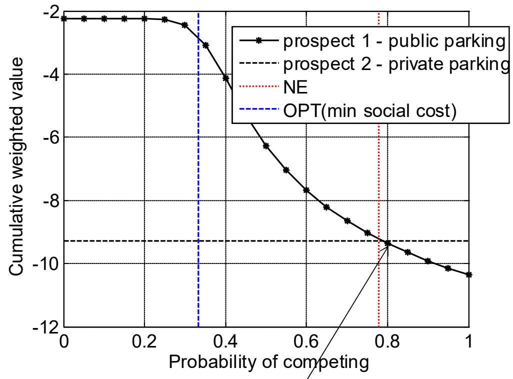
$$g_l(k) = min(1, R/k)c_{l,s} + (1 - min(1, R/k))c_{l,f}$$

and the probabilities p_k for this are Binomial (N, p_l^{CPT})

Both prospects consist of negative outcomes / costs

Applying CPT to Resource Selection Problem

- N= 150 , R=50
- $c_{osp,s} = 1$
- $\beta = 5$ ($c_{pl} = 5$)
- $\gamma = 8$
- $\delta = 3$



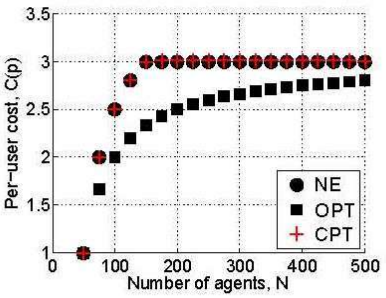
CPT eq: 0.79 NE: 0.78 OPT: 0.33

CPT equilibrium condition :

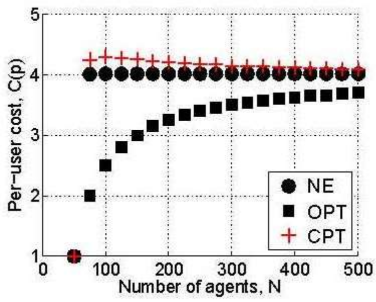
CPT value of prospect 1 = CPT value of prospect 2

Some results

R=50 (δ=1, low risk) (δ=16, high risk)



(a) $\beta = 3, \gamma = 4$



(c) $\beta = 4, \gamma = 20$

- Small deviation from the full rationality framework
- More risk-prone behavior under high penalty cost (δ)
  - Competing probabilities: NE: 0.59 , CPT: 0.61
- Both full rational (NE) and biased (CPT) practices are more costly than OPT

Deviations from Full Rationality

- (Cumulative) Prospect Theory
  - maintains most of the concepts/assumptions of EUT
  - manipulates both utility measures and prob. to account for biases against risk

- **Alternative decision-making models & Equilibrium (EQ) concepts (Quantal Response, Rosenthal)**
  - Use probabilistic choice models to capture any unobserved and omitted elements, estimation/computational errors, individual's mood, perceptual variations or cognitive biases
  - In line with the fact that individuals are more likely to make better choices than worse choices, but do not necessarily make the very best choice

- Heuristics
  - Fast and frugal reasoning solutions / decisions
  - Emphasis on cognitive processes underlying decisions

Quantal response equilibrium (McKelvey & Palfrey, 1995)

- "Individuals are more likely to select better choices than worse choices, but do not necessarily succeed in selecting the very best choice."
  - Due to noise/disturbances in their anticipation of exact choices' payoffs

- Introduce some **randomness in the decision-making process** to capture people's inability to play always the strategy that maximizes the expected utility
  - "Choices are made with probabilities that are monotone in their expected payoffs"
  - Logit QRE => disturbances/errors follow extreme value distribution (smaller mistakes are more likely to occur that more serious ones)

$$p(r_1) = \frac{e^{-\lambda EU(r_1)}}{e^{-\lambda EU(r_1)} + e^{-\lambda EU(r_2)}}$$

$$p(r_1) = 1 - p(r_2)$$

$\lambda \in [0, \infty]$: rationality control parameter
$\lambda \rightarrow 0$: random decision
$\lambda \rightarrow \infty$: full rationality (Nash EQ)
[cost differences (i.e., *EU*(.)) are emphasized more through a more responsive distribution to cost changes, in line with the more emphasis in differences expected by a more rational decision-maker.]

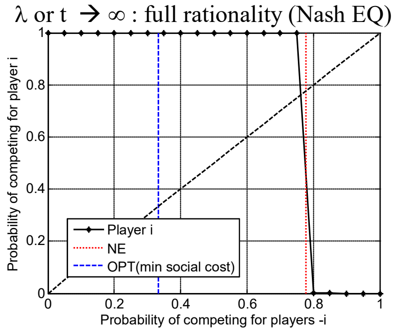
Quantal response equilibrium for Resource Selection Problen

$$p_l^{QRE} = \frac{e^{-tc(l,p^{QRE})}}{e^{-tc(l,p^{QRE})} + e^{-tc(u,p^{QRE})}} \qquad c(l,p) = \sum_{n=0}^{N-1} g_l(n+1)B(n;N-1,p_l)$$

$$p^{QRE} = (p_l^{QRE}, p_u^{QRE}),\ p_u^{QRE} = 1 - p_l^{QRE} \qquad c(u,p) = c_u$$

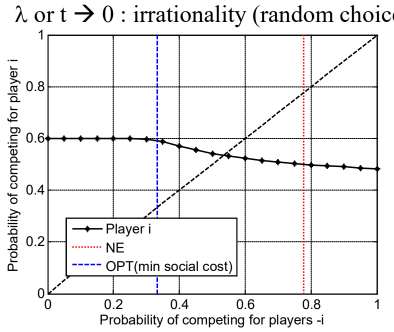
At EQ, prob of competing of player i equals the belief for the way (i.e. prob) the others play which is used in calculating c(l,p)

λ or t → ∞ : full rationality (Nash EQ)



QRE: 0.77 NE: 0.78 OPT: 0.33

λ or t → 0 : irrationality (random choice)



QRE: 0.55 NE: 0.78 OPT: 0.33

Rosenthal equilibrium (Rosenthal, 1989)

"The difference in probabilities with which two actions are played equals a parameter *t* multiplied by the difference of the corresponding expected costs"

$$p(r_1) - p(r_2) = t(EU(r_1) - EU(r_2))$$

$$p(r_1) = 1 - p(r_2)$$

t ∈[0,∞] : rationality control parameter
t → ∞ : full rationality

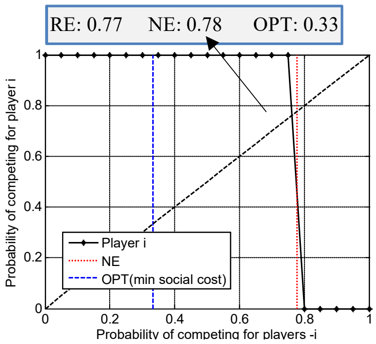
Rosenthal equilibrium for Resource Selection Problem

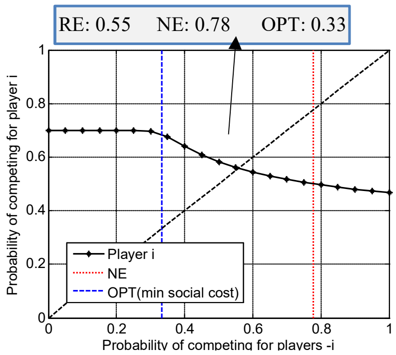
$$p_l^{RE} - p_u^{RE} = -t(c(l, p^{RE}) - c(u, p^{RE}))$$

$$p^{RE} = (p_l^{RE}, p_u^{RE}),\ p_u^{RE} = 1 - p_l^{RE}$$

t → ∞ : full rationality (NE)

t → 0 : no rationality (random choice)

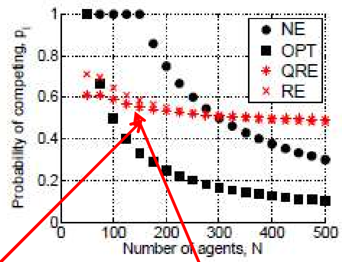


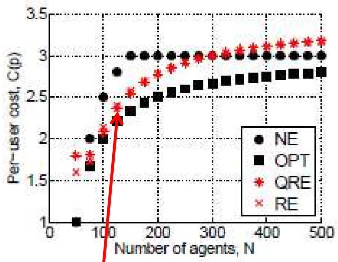


Some results

Very low rationality level (t = λ= 0.2)

- R=50
- $c_{osp,s}$ =1
- β = 3 (c_{pl} = 3)
- γ=4
- δ = 1
- t = λ= 0.2





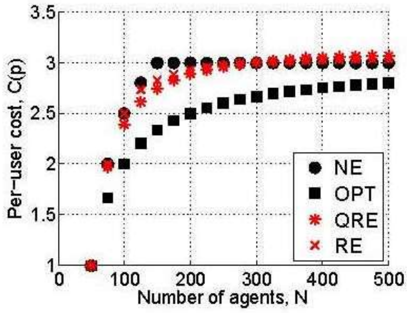
Competing prob close to .5 (random choice)
Rationality parameter close to 0

under low/medium demand (N<300)
the inaccuracies in computing the best action as modeled in these equilibrium concepts decrease the competing probability and hence,
the per-user cost in these cases is drawn to near-optimal levels.

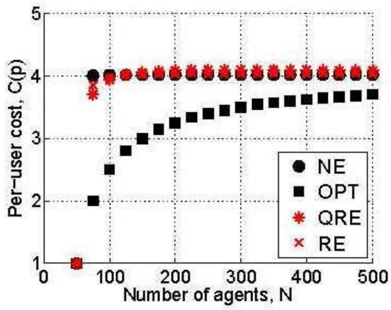
Some results

Med-high rationality level (t = λ= 3)

R=50 , $c_{osp,s}$=1 , t = λ= 3



β = 3 (c_{pl} = 3), γ=4



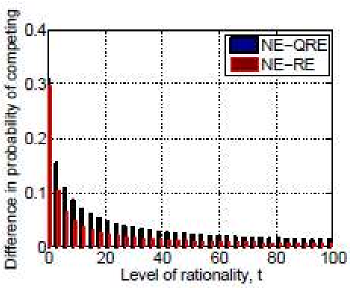
β = 4 (c_{pl} = 4), γ = 20

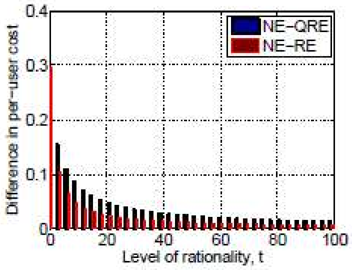
- RE and QRE costs closer to NE
- The higher the difference of - expected - costs of the two options, the less RE and QRE differ from NE, since the identification of the best action becomes easier.

Some results

Impact of rationality on difference of competing probabilities (QRE-NE and RE-NE)

R=50 , $c_{osp,s}$=1, β = 3 (c_{pl} = 3), γ=4, N=180, **t = λ in [0.1,100]**





Deviations from Full Rationality

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  - Use probabilistic choice models to capture any unobserved and omitted elements, estimation/computational errors, individual's mood, perceptual variations or cognitive biases
  - In line with the fact that individuals are more likely to make better choices than worse choices, but do not necessarily make the very best choice
- **Heuristics**
  - Fast and frugal reasoning solutions / decisions
  - Emphasis on cognitive processes underlying decisions
  - Satisfying instead of maximization of expected utilities (Simon 1955)

Heuristic strategy for the resource selection problem

Satisficing: instead of computing/comparing expected costs, it estimates the probability to hit an empty public spot and plays according to this.

***Confidence* heuristic rule**: "risk competing for resource r_1 according to the probability of winning one of the R resources"

- Under the belief that other players think the same way

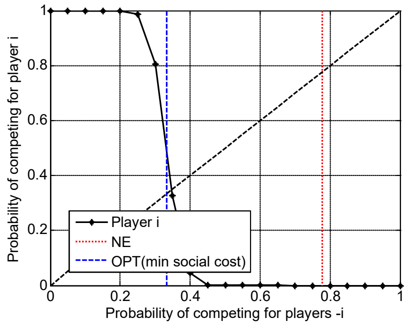
- Fixed-point equation

$$p(r_1) = \Pr(\#competitors < R) = \sum_{j=0}^{R-1} Bin(j, N-1; p(r_1))$$

Heuristic strategy for the resource selection problem

- *Confidence* heuristic: "risk for public parking space according to the probability of winning public parking space"

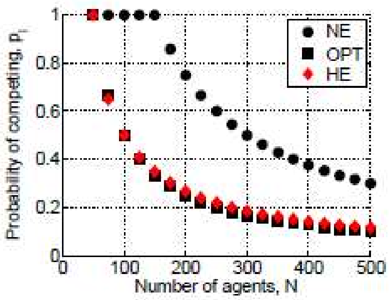
$$p_{osp} = \Pr(\#competitors < R) = \sum_{j=0}^{R-1} Bin(j; N-1, p_{osp})$$

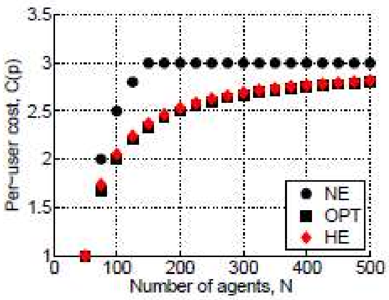


$$HE = 0.34, NE = 0.78, \mathrm{OPT} = 0.33$$

Some results

Confidence heuristic





- Yields near-optimal results
- Implicitly seeks to avoid tragedy of commons effects

Conclusions for the models of bounded rationality

Formulation of the parking spot selection application drawing on models from behavioral economics and cognitive psychology

- **(Cumulative) Prospect Theory** :
  - The decision maker is still a utility maximizer
  - The desirability of outcomes is expressed through the transformed probabilities of them
  - Small deviation from the full rationality framework
- **Alternative equilibrium concepts (Quantal Response Equilibrium, Rosenthal equilibrium)**
  - The decision maker is a satisfizer
  - Symmetric mixed-action equilibria as fixed-point solutions
  - A degree of freedom quantifies the rationality in the model (convergence to the Nash equilibrium as the free parameter goes to infinity)
- **Heuristics**
  - The decision maker is a satisfizer
  - Confidence heuristic: fast and frugal reasoning solution that is shown to yield near-optimal results within the particular application concept

Part A
Decision-making in Distributed, Uncoordinated, Resource-limited ,Competitive Environments


With **some cost if trying but failing to find a resource** (spot)


Major Question posed

TO COMPETE OR TO NOT COMPETE?

that is the question

- *to compete for a limited-inexpensive resource or go for the unlimited, expensive alternative?*

*(cost of failure: usage of the expensive resource **PLUS paying a failing penalty**)*

Part A
Decision-making in Distributed, Uncoordinated, Resource-limited ,Competitive Environments

PART B
Congestion-cost-cutting Approaches In Resource-limited Competitive Environments

PART B
Congestion-cost-cutting Approaches In Resource-limited Competitive Environments

CASE B-1
Coordinated Resource Allocation through Auction-based Systems

Resolve competition in the pricing arena

*E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, **"Trading public parking space"**, IEEE WoWMoM workshop on Smart Vehicles, June 16-19, 2014, Sydney, Australia.*

Coordinated Resource Allocation through Auction-based Systems

Eliminate (competition-induced) cruising cost,
by ***replacing the physical competition for a public parking spot***
by a ***competition for the price to be paid***

Winners will pay a higher price for the public spot ($[c_{pub,s}, c_{priv}]$), but
Losers will not pay any cruising cost

On average,
can drivers do better under the auction-based mechanism?

Trading public parking space: auction-based allocation

- N drivers (**buyers, bidders**)
- S: spare on-street public parking spots (**non-divisible, physically identical goods**)

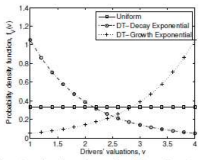
- Public parking operator (**auctioneer**)
  - –gets informed about the status of public spots
  - –collects requests and drivers' bids for public spots
  - –determines parking spot allocations, payments
  - –notifies the winners

… *through sensor networks and wireless communications*

(Parking Auction, Monkey Parking, etc)

1. Bidding

- Drivers:
  - –bid for no more than one of S public spots
  - –seek to maximize their expected profit from bidding (risk-neutral bidders)
  - –free of budget constraints
- Bids: increasing functions of drivers' valuations of parking spots
- Valuations:
  - –Independent and private valuations
  - –i.i.d RVs continuously distributed *within [vmin, vmax]* = *[**cpub,s, cpriv**]*
  - –-3 different distributions are considered:



Distribution of drivers' valuations	$f_V(v)$
Uniform	$\frac{1}{v_{max}-v_{min}}$
Doubly-truncated *decay* exponential	$\frac{e^{-v}}{e^{-v_{min}}-e^{-v_{max}}}$
Doubly-truncated *growth* exponential	$\frac{e^{v}}{e^{v_{max}}-e^{v_{min}}}$

Probability density functions for drivers' valuations of public parking spots, $c_{pub,s} = 1$, $\beta = 4$.

2. Allocation rule: who are awarded parking spots

3. Payment rule: the selling price of each allocated spot

Multi-unit auctions with single-unit demand

- Uniform-price, Vickrey auctions
- Discriminatory-price auctions

Allocation rule in the equilibrium

All auction formats follow the same allocation rule, that is, they assign the spots to the users that

- submit the highest bids (standard auctions)
- value the public spots most (efficient auctions)

Payment rule in the equilibrium

- Uniform-price, Vickrey auctions (upa):
  –all parking spots are sold at the same price which is equal to the first losing bid
- Discriminatory-price auctions (dpa):
  –the winning drivers pay an amount equal to their individual bids

Bidding in the equilibrium

- Uniform-price, Vickrey auctions (upa):
  The drivers bid their real valuations (truthful mechanisms)
- Discriminatory-price auctions (dpa):
  The drivers bid the expected value of the first losing bid, assuming that theirs was the highest

Trading Public Parking Space: Auction-based Allocation

Are the 2 bodies better off ?
(wrt the uncoordinated approach)

1. Is the public spot operator doing better? (*Revenue*)
2. Is the average driver doing better? (*Aggregate Cost*)

Revenue and Aggregate cost in the equilibrium

- **Auction-based allocation:**

–**Revenue (i.e., income of the public parking lot operator)**

$$R_a \equiv E\{R_{upa}\} = E\{R_{va}\} = E\{R_{dpa}\} = SE\{V_{(N-S,N)}\}$$

–**Aggregate cost (of all drivers)**

$$C_a \equiv E\{C_{upa}\} = E\{C_{va}\} = E\{C_{dpa}\} = SE\{V_{(N-S,N)}\} + (N-S)v_{max}$$

***$E\{V_{(N-S,N)}\}$ = expected value of the (N-S) order statistic of the N competing valuations = first losing bid = expected payment for a single spot

- **Uncoordinated strategic parking spot selection game:**

–**Revenue (i.e., income of the public parking lot operator)**

$$R_g \equiv R(N) = \min(N,S)c_{pub,s}, \text{ if } N \le N_0 \text{ and}$$

$$R_g \equiv R(N_0) = Sc_{pub,s}, \text{ if } N > N_0$$

–**Aggregate cost (of all drivers)**

$$C_g \equiv C(N) = c_{pub,s}\left[N\gamma - \min(N,S)(\gamma-1)\right], \text{ if } N \le N_0 \text{ and}$$

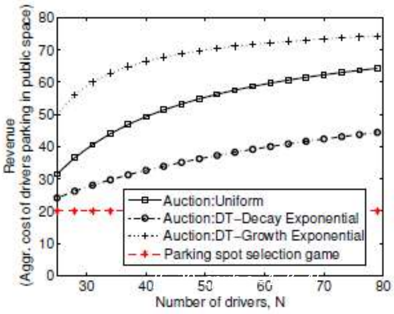
$$C_g \equiv C(N_0) = c_{pub,s}\beta N, \text{ if } N > N_0$$

$$N_0 = \frac{S(\gamma-1)}{\delta}$$

Numerical results – On the public operator's side

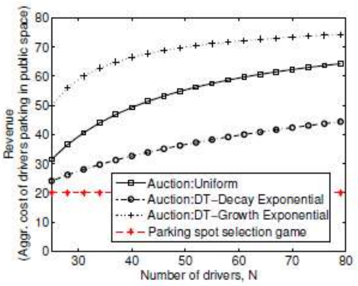
The revenue from auctioning exceeds that under the fixed-cost uncoordinated parking service provision

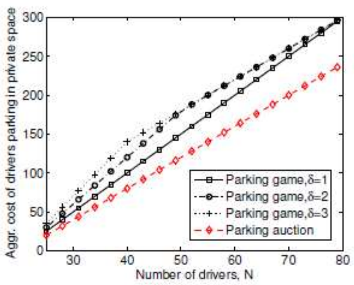
- the same number of drivers park in public space under both practices
- drivers pay at least $c_{pub,s}$ in the auction and exactly $c_{pub,s}$ in the uncoordinated game



❖ *The operator always does better under the auction-based mechanism*

Numerical results – On the driver's side





1. Aggr. cost of drivers parking in **public** space under the auctioning system exceeds that under the uncoordinated game (left fig.)
2. Aggr. cost of drivers parking in **private** space under the auctioning system is lower than that under the uncoordinated game, *due to the **savings of the "price of anarchy"*** (right fig.)

If congestion penalty exceeds excess cost from bidding over a minimum cost (cpub,s), then drivers as well do better under the auction-based mechanism

➔ ***Win-Win situation for both the operator and the drivers***

Win-win Conditions under High Demand (?)

- Difference on per-user costs: $\Delta = \frac{1}{N}(C_g - C_a)$
- Win-win situations if $\Delta > 0$

- Case : $N > N_0,\ N_0 = S(\gamma - 1)/\delta$

$$\Delta \;=\; \frac{S}{N}(\beta c_{pub,s} - E\{V_{N-S,N}\}) > 0$$

since the per-spot expected payment *E{V(N-S,N)}* is strictly smaller than the cost of private parking space β $c_{osp,s}$. Therefore, drivers are always better off under the auctioning system.

ALWAYS!

Win-win Conditions under Low - Medium Demand (?)

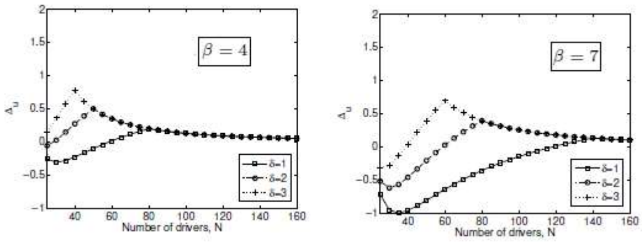
- Case $N \le N_0,\ N_0 = S(\gamma - 1)/\delta$:

$$\Delta \;=\; \frac{1}{N}\left[c_{pub,s}[N\gamma - S(\gamma - 1)] - C_a\right]$$

– **Uniformly distributed valuations**

$$\Delta_u = \; c_{pub,s}\frac{(N-S)}{N}\left[\delta - (\beta - 1)\frac{S}{N+1}\right]$$

- **Δu increases with δ**: Any increase in δ raises the "price of anarchy"
- **Δu decreases with β**: Any increase in β raises the payments in the auctioning system and hence, reduces the advantage of saving the cruising cost



S=20

Win-win situations might emerge under proper pricing and failure costs, so that $\Delta_u > 0$

Conclusions

- **Investigate effectiveness of auctioning systems in the parking spot allocation in terms of**
  - (a) induced drivers' aggregate cost
  - (b) operator's revenue
- **Considered:**
  - uncoordinated strategic parking spot selection game vs.
  - multi-units auctions with single-unit demand: uniform-price, Vickrey and discriminatory-price auctions
- **Guaranteed higher profits for operator**
- **Guaranteed win-win situations, under high demand, or possible with proper pricing/failure costs, otherwise**

PART B
Congestion-cost-cutting Approaches In Resource-limited Competitive Environments

CASE B-1
Coordinated Resource Allocation through Auction-based Systems

Resolve competition in the pricing arena

PART B
Congestion-cost-cutting Approaches In Resource-limited Competitive Environments

CASE B-2
Coordinated Resource Allocation through Social Applications

Resolve competition through ICT and IoT

*E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, **"Parking assisting applications: effectiveness and side-issues in managing public goods"**, 3rd AWARE workshop on Challenges for Achieving Self-Awareness in Autonomic Systems of the Self-Adaptive and Self-Organizing systems conference (SASO 2013), Sept. 9-13, 2013, Philadelphia*

Decentralized Resource Allocation through Social Applications

User would subscribe to be able to more effectively use public resources in a competitive environment

Social apps for parking resources:

(Sfpark, **Parking Defenders**, Parkomotivo)

Some important questions

Are these apps effective and "fair" to their users?

- Do they require high user subscription to be effective?
- Do they treat equally similar users?
- **Do they create a wealth (through coordination and congestion cost cutting) that rightfully distribute to their users?**
  - **Or simply benefit by eliminating competition by non-users (exclusion)?**

What is the ***impact on non-users***?

- Are non-users of these apps suffering substantially
  - (or almost excluded from) accessing **public goods**?

3 Driver profiles

- **Traditional** user/driver (non-users of the application)
- App user/driver:
  - **Defender** (sharer, fully cooperative)
    - Announces upcoming freed-up spot
    - Waits for selected app user to come
    - Rates other defender upon parking
    - Earns credit and improves its ranking
  - **Seeker** (free rider – not fully cooperative)
    - Rates defender upon parking

Effectiveness of the social parking application: low to moderate parking demand (45% , 75%)

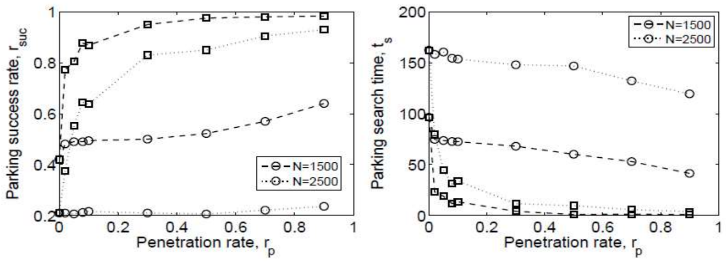
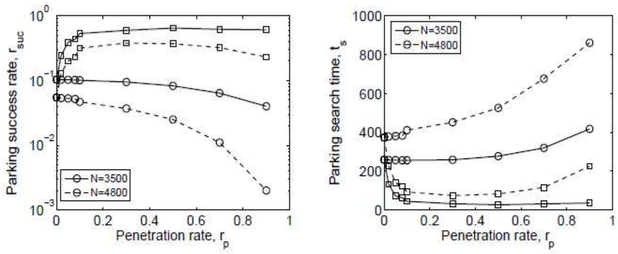


Fig. 3. Performance indices for Non-users (circles) and Sharers (squares) at low to moderate parking demand: $n_{FR} = 0\%$.

- Application users ***experience better performance*** than traditional driver
- The advantage for Defenders emerges ***even at low penetration rates***
- **Win – win situations**: Non-users also improve their performance!

(the effective competition that non-users experience is mitigated)

Effectiveness of the social parking application: Very high parking demand (105%, 145%)



a. Parking success rates b. Parking search times

Performance indices for Non-users (circles) and Sharers (squares) at high parking demand:

At high penetration rates:

- Non-user exclusion trends
- Sharer performance deterioration due to own competition

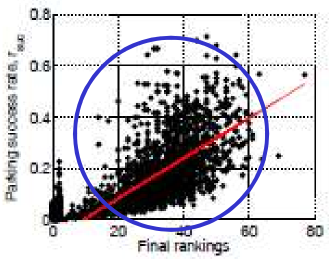
Effectiveness of the incentive mechanism and some concerns on its fairness

It is ***effective***…

- higher success rates are coupled with higher rankings

But ***not fair***…

- it discriminates against identical users (=users with similar interests, needs and attitude towards cooperation)
- It induces **rich-get-richer phenomena**: winners in the initial competition round earn credits that offer them a competitive edge in the following rounds

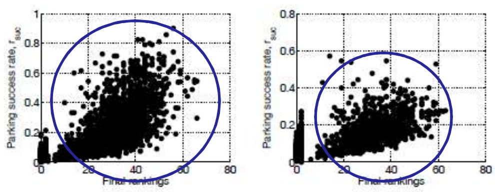


Impact of Seekers on the incentive mechanism's fairness

Seekers tend to ***restore fairness***

↑ Seekers' portion → ↓ parking spot handovers →

↓ opportunities for credit-building/emergence of high rankings



a. $r_s = 30\%$ b. $r_s = 70\%$

Conclusions

Investigated effectiveness / appropriateness of distributed, social public resource (parking) management apps

- **Effective and mostly non-exclusive to non-users**
  - Users' improved performance is mostly due to the **increased efficiency they generate in the parking process, rather than excluding** traditional users from competing for the resources.
  - **Non-Users also benefit from the reduced anarchy** and coordination that the App brings
- Incentive mechanism is effective
  - But it induces rich-club phenomena and difficulties to newcomers
- Seekers (free-riders) seem to alleviate those problems

SUMMARY of Resource Competition in a Highly Networked World of Humans and Things

Motivation (environment – early study)

Decision-making in uncoordinated competitive environment - formulation
- **rational case – Price of Anarchy**
- **limited info case**
- **human driven case**
  - **Prospect Thy**
  - **alternative models**
  - **heuristics**

Alternative, partially coordinated approaches
- **Auctioning resources**
- **ICT-supported distributed apps**