Introduction – Chris Develder

- PhD, Ghent University, 2003
  - "Design and analysis of optical packet switching networks"
- Professor at Ghent University since Oct. 2007
  - *Research Interests*: **smart grids** (optimization/scheduling algorithms for DSM/DR; data analytics), **information retrieval/extraction** (e.g., knowledge base population, event relations in news archives); **optical networks** (dimensioning, resilience schemes, ILP)
  - Visiting researcher at UC Davis, CA, USA, Jul-Oct. 2007 (optical grids)
  - Visiting researcher at Columbia Univ., NY, USA, 2013-14 (IR/IE)
- Industry Experience: network planning/design tools
  - OPNET Technologies (now part of Riverbed), 2004-05
- More info: http://users.atlantis.ugent.be/cdvelder

Smart grid algorithms: Knowing and controlling power consumption

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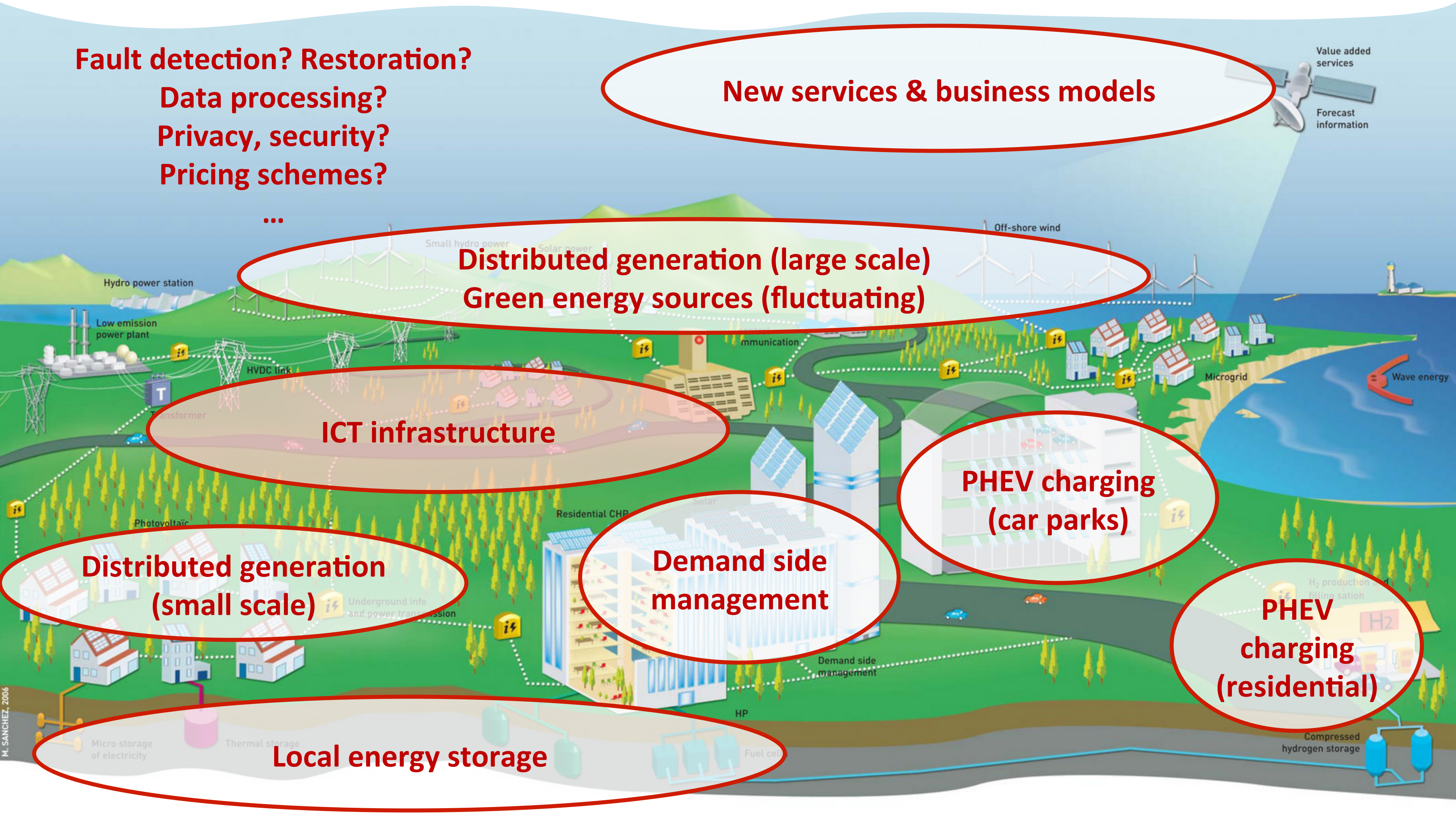
Dept. of Information Technology – IBCN

Smart Grids

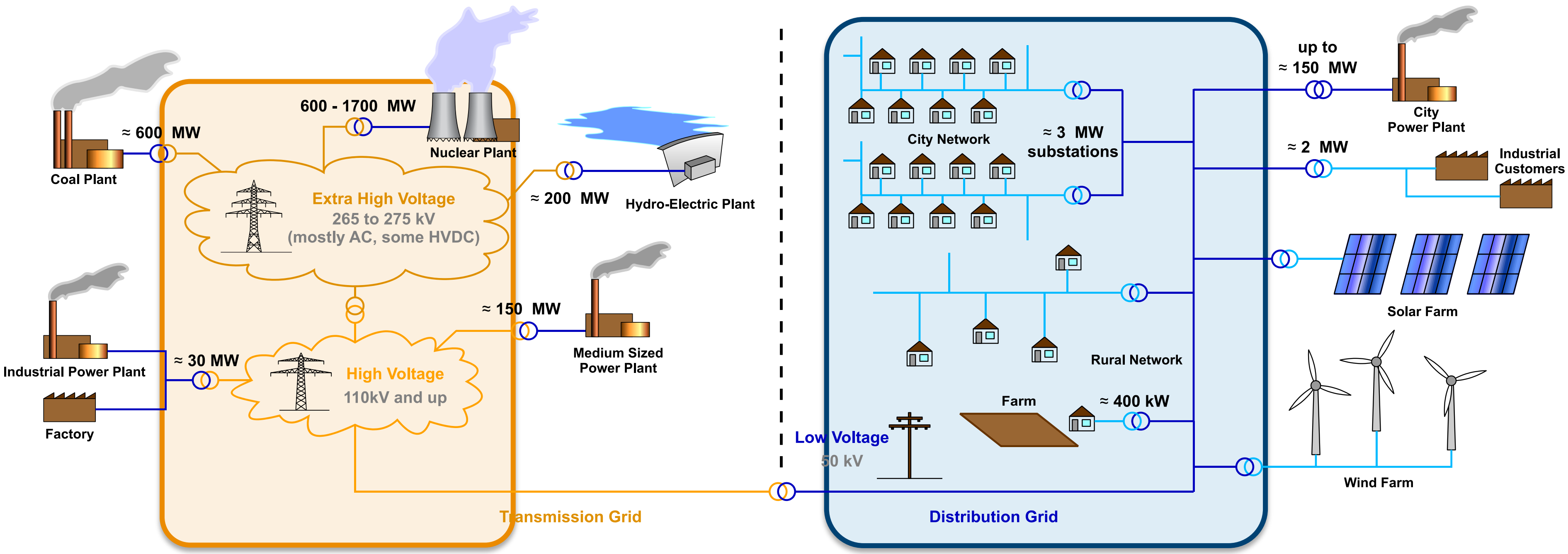


Fault detection? Restoration?
Data processing?
Privacy, security?
Pricing schemes?
...
New services & business models
Value added services
Forecast information
Distributed generation (large scale)
Green energy sources (fluctuating)
Off-shore wind
Hydro power station
Low emission power plant
HVDC link
ICT infrastructure
Microgrid
Wave energy
PHEV charging
(car parks)
Residential CHP
Photovoltaïc
Distributed generation
(small scale)
Demand side
management
Demand side management
PHEV
charging
(residential)
HP
Local energy storage
Compressed hydrogen storage
M. SANCHEZ, 2006

Power grid structure

Transmission network (operated by TSO)

Distribution network (operated by DSO)



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Outline

1. Introduction

Part I: Algorithms for DSM/DR

2. Example 1: Peak shaving
3. Example 2: Wind balancing
4. Tools to study smart grid cases

Part II: Data analytics

5. Clustering smart metering data
6. EV usage analysis

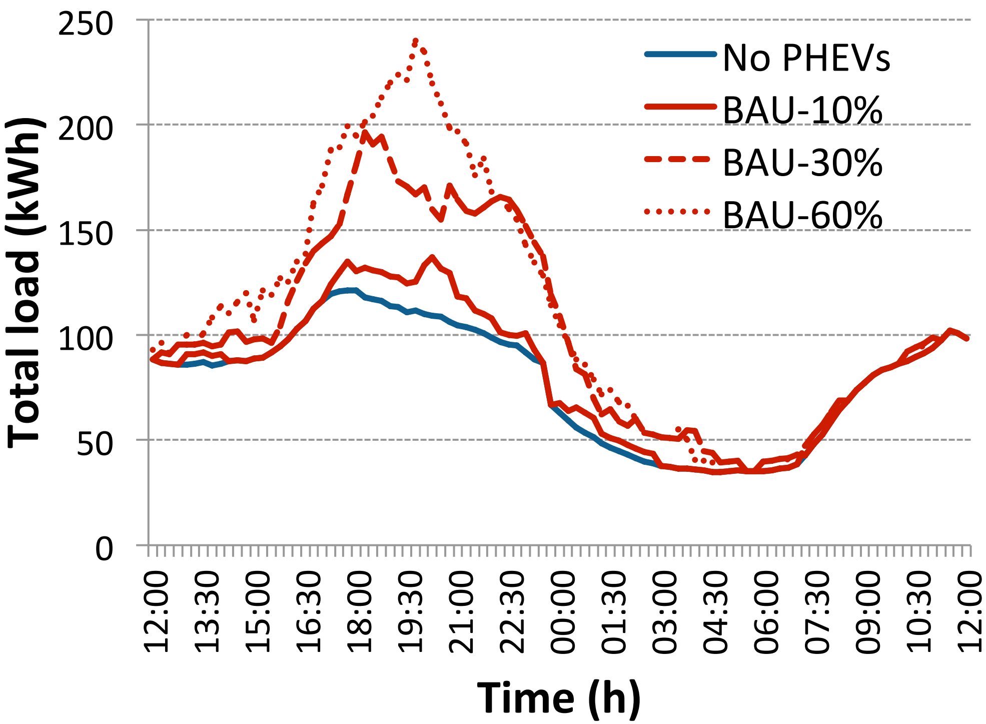
K. Mets, R. D'hulst and C. Develder, ***"Comparison of intelligent charging algorithms for electric vehicles to reduce peak load and demand variability in a distribution grid"****, J. Commun. Netw., Vol. 14, No. 6, Dec. 2012, pp. 672-681. doi:10.1109/JCN.2012.00033*

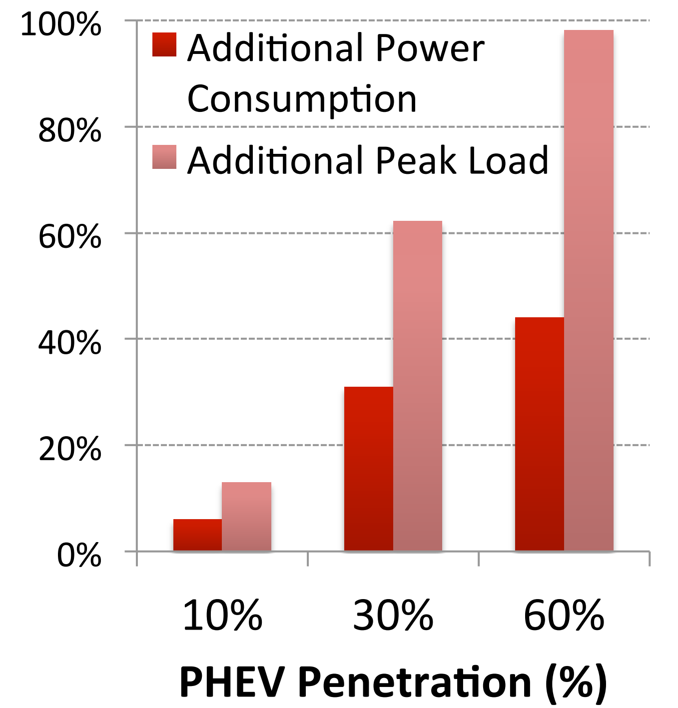
Example case study: EV charging

- Research questions:
  1. Impact of (uncontrolled) EV charging in a residential environment?
  2. Minimal impact on load peaks we could theoretically achieve?
  3. How can we minimize the impact of EV charging in practice?

Impact of EV charging

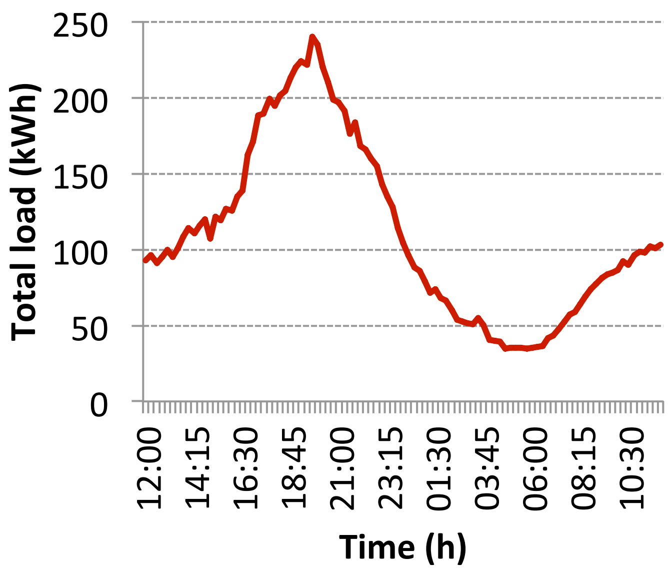
- Sample analysis for 150 homes, x% of them own a PHEV
- BAU = maximally charge upon arrival at home

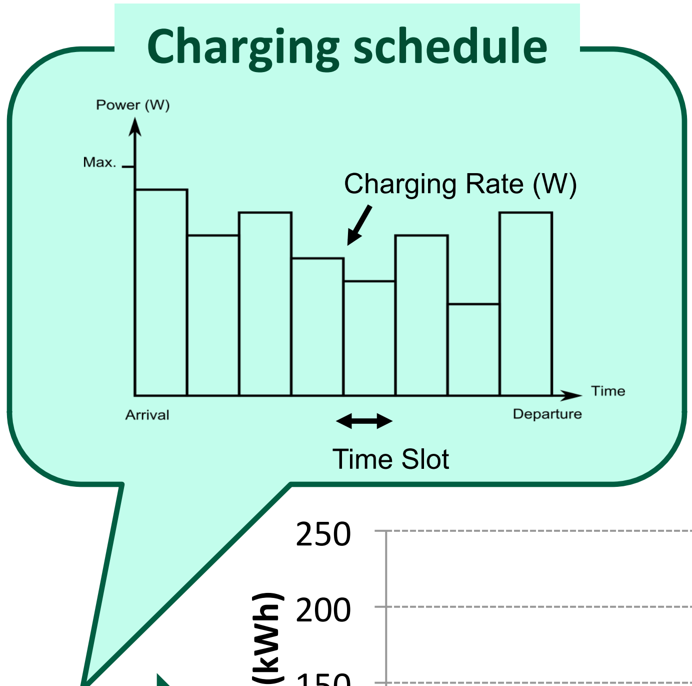


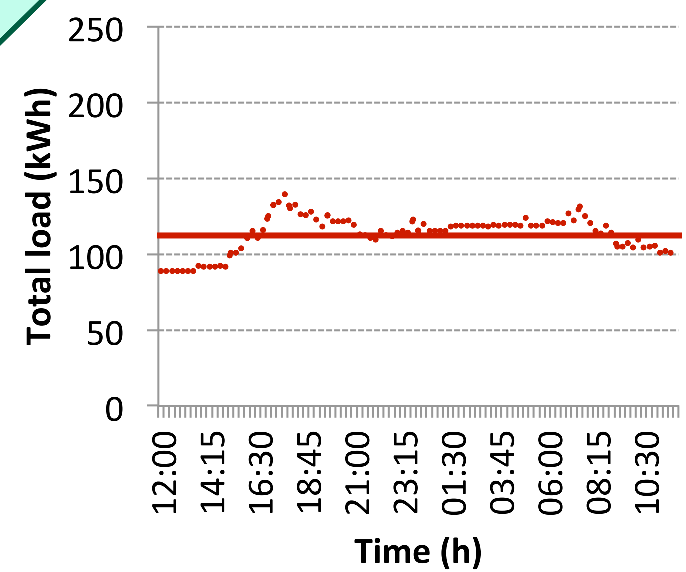


Controlling EV charging?

- Objectives:
  - Reduce peak load
  - Flatten (total) load profile (= reduce time-variability)
  - Avoid voltage violations







Smart charging algorithms

Quadratic Programming (QP)

- Offline algorithm
- Planning window
- "Benchmark"
- Three approaches:
  - Local
  - Iterative
  - Global

Multi-Agent System (MAS)

- Online algorithm
- No planning window
  → current time slot info only
  (but EV bidding changes when charging deadline approaches)
- "Realistic"
- Single approach

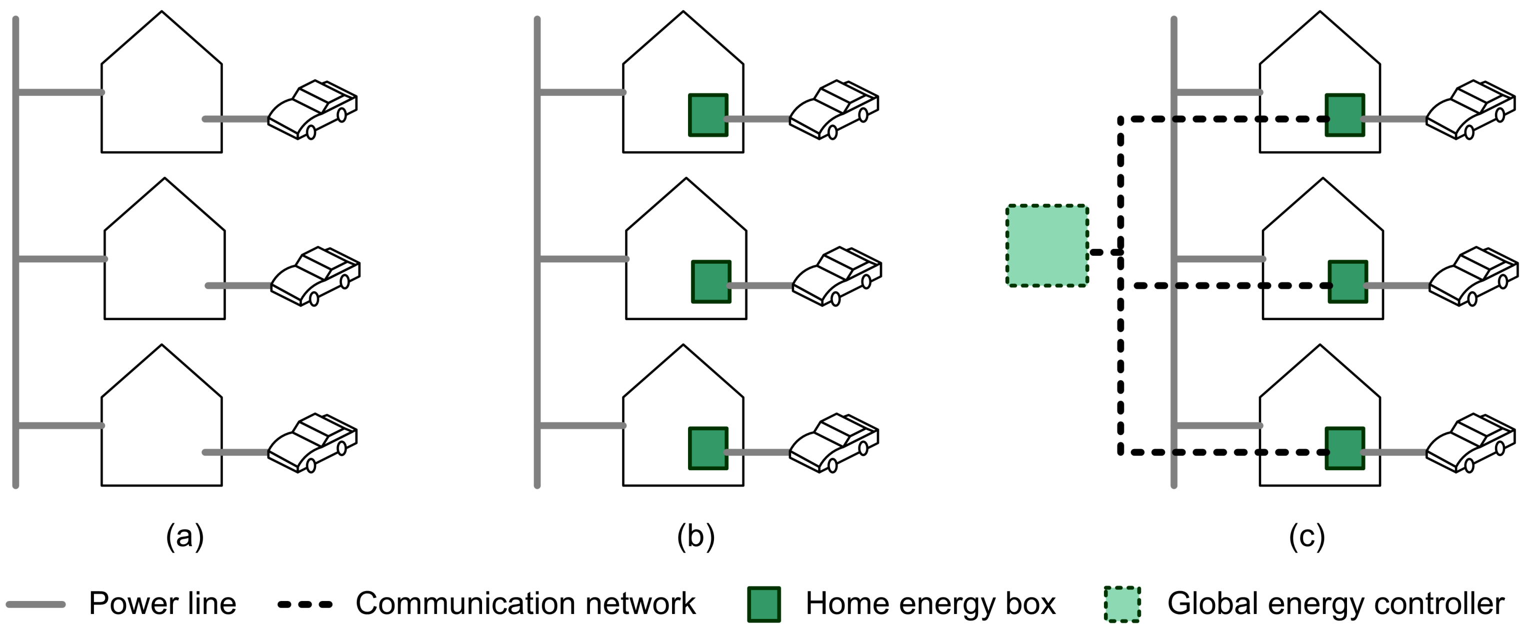
Reference scenario: Uncontrolled charging

Smart charging: QP

BAU
(uncontrolled)

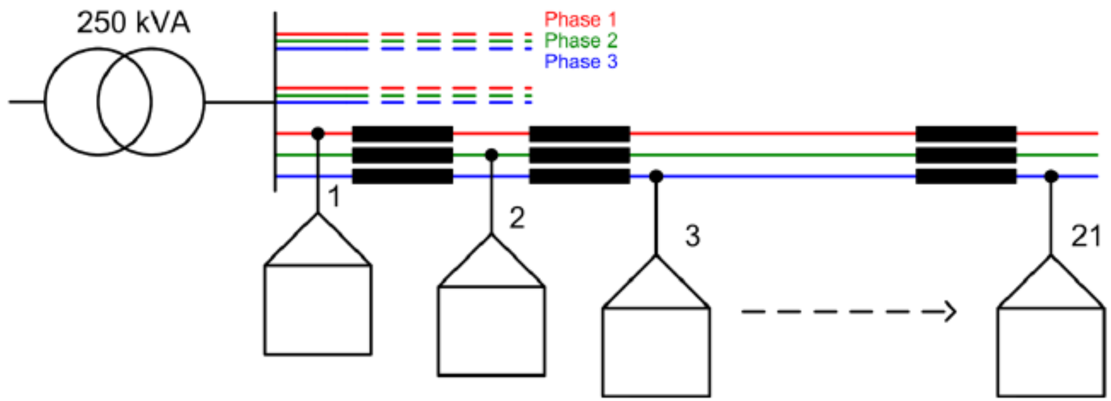
Local control (QP)

Global control (QP), Market MAS



Case study

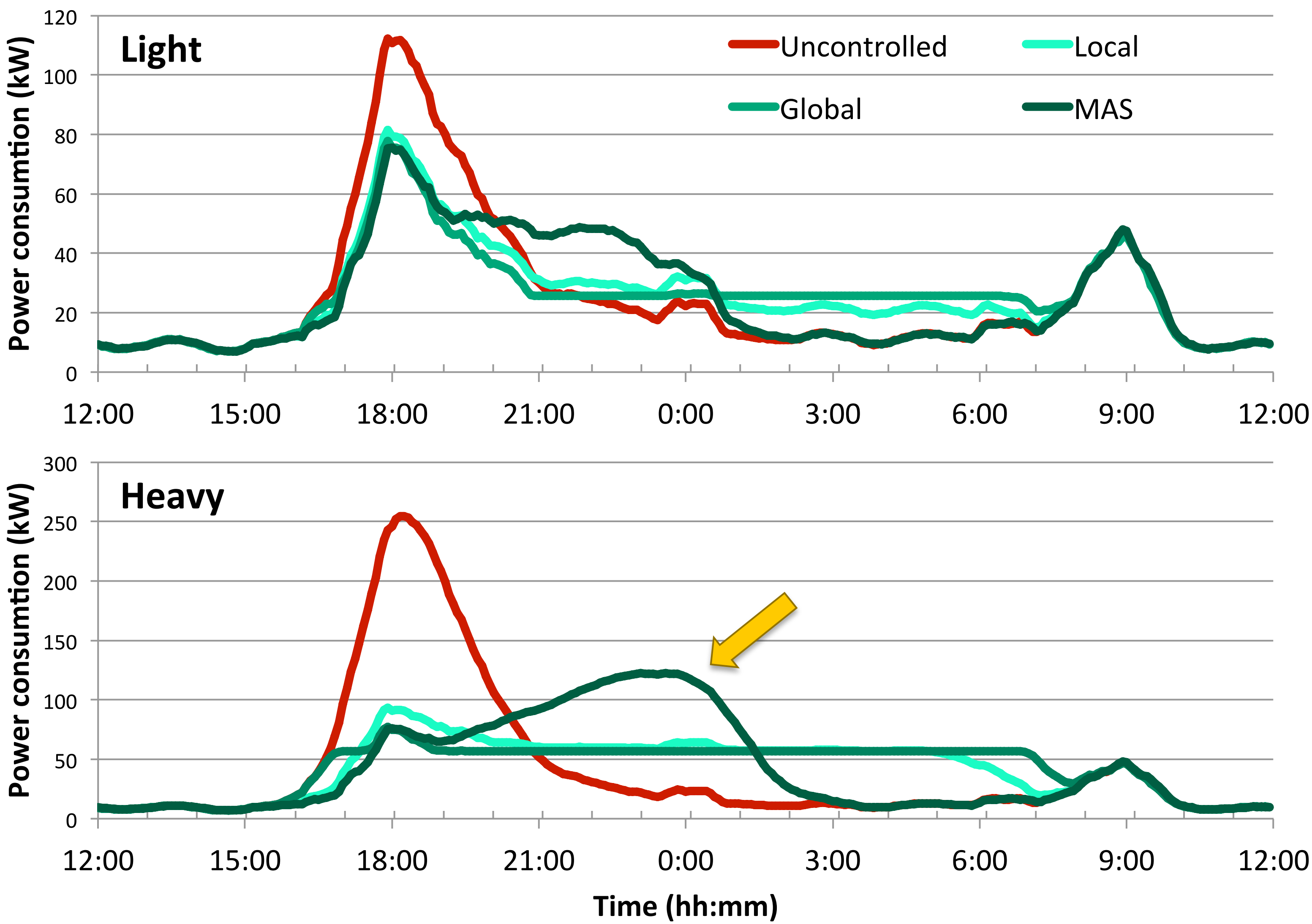
- 63 Households
  - Randomly distributed over 3 phases
  - Spread over 3 feeders



- Electrical vehicles
  - PHEV: 15 kWh battery
  - Full EV: 25 kWh battery
  - Randomized arrivals (~5pm) and departures (~6am)

Scenario	PHEV 3.6 kW	PHEV 7.4 kW	EV 3.6 kW	EV 7.4 kW
Light	4	3	2	1
Medium	10	10	5	4
Heavy	17	16	7	7

Results (1) – Load profiles



Results (2) – Load peaks & variability

	Peak Load ↘			
Scenario	QP1	QP2	QP3	MAS
Light	29.62%	32.16%	32.16%	32.00%
Medium	53.84%	58.73%	58.73%	53.19%
Heavy	63.76%	70.00%	70.00%	54.04%

	Standard deviation ↘			
Scenario	QP1	QP2	QP3	MAS
Light	35.24%	41.63%	41.94%	25.29%
Medium	55.01%	60.50%	61.88%	34.91%
Heavy	60.22%	63.82%	65.84%	38.80%

QP1 = local QP2 = iterative QP3 = global

Results (3) – Voltage deviations

Table 6. Average number of 5 minute time slots (out of the 288 time slots over the course of the considered one day period) during which voltage deviations exceeding 10% are observed.

Scenario	BAU	QP1	QP2
Light	22.17	3.90	3.31
Medium	38.01	4.52	5.32
Heavy	45.51	3.92	9.30

Note: 10 slots ~ 3.4% of the time

Not solved entirely!
(No explicit part of objective function!)

Table 7. Average and maximum magnitude of voltage deviations.

	BAU		QP1		QP2	
Scenario	AVG	MAX	AVG	MAX	AVG	MAX
Light	20%	29%	13%	19%	13%	18%
Medium	29%	60%	13%	22%	13%	20%
Heavy	37%	65%	12%	20%	14%	22%

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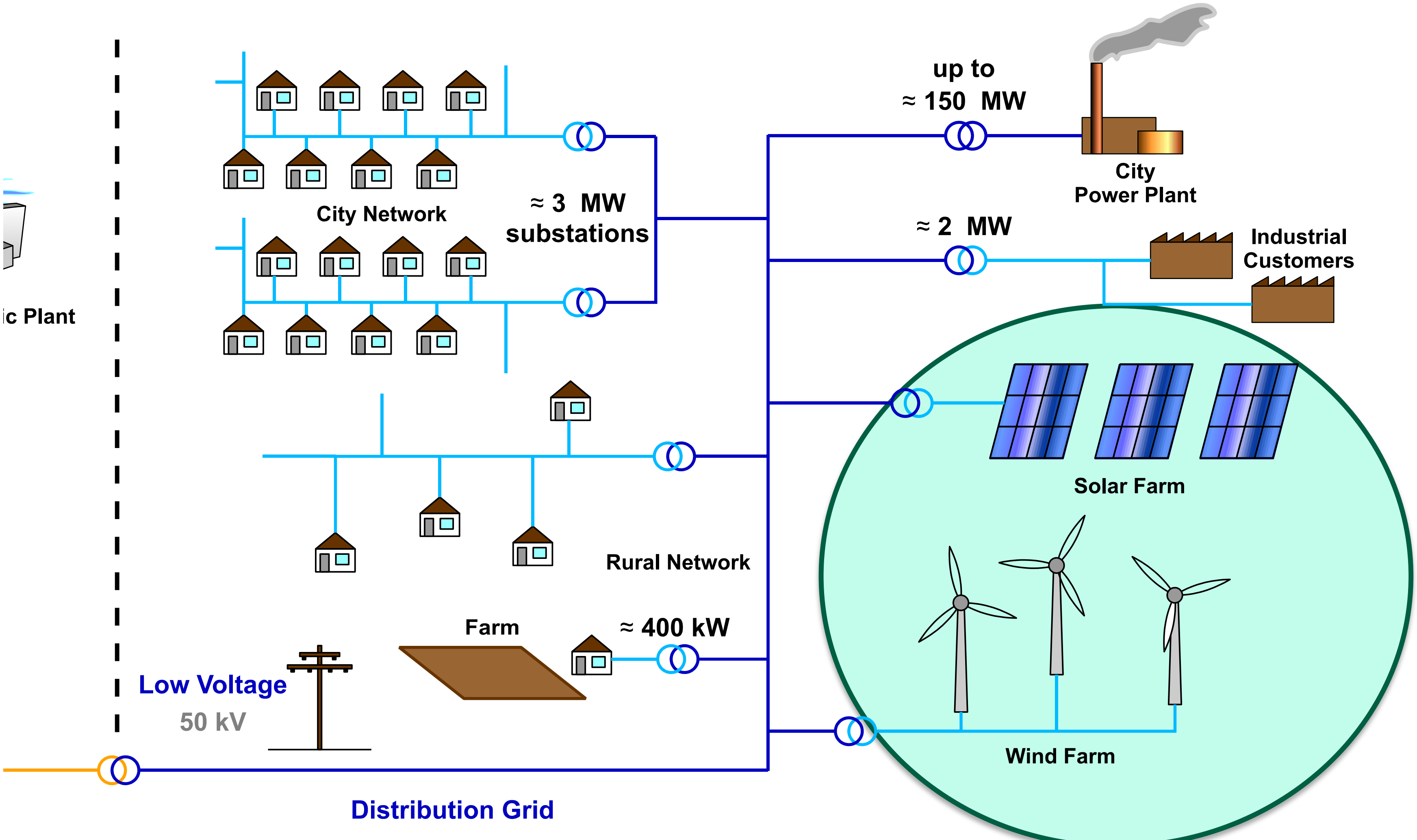
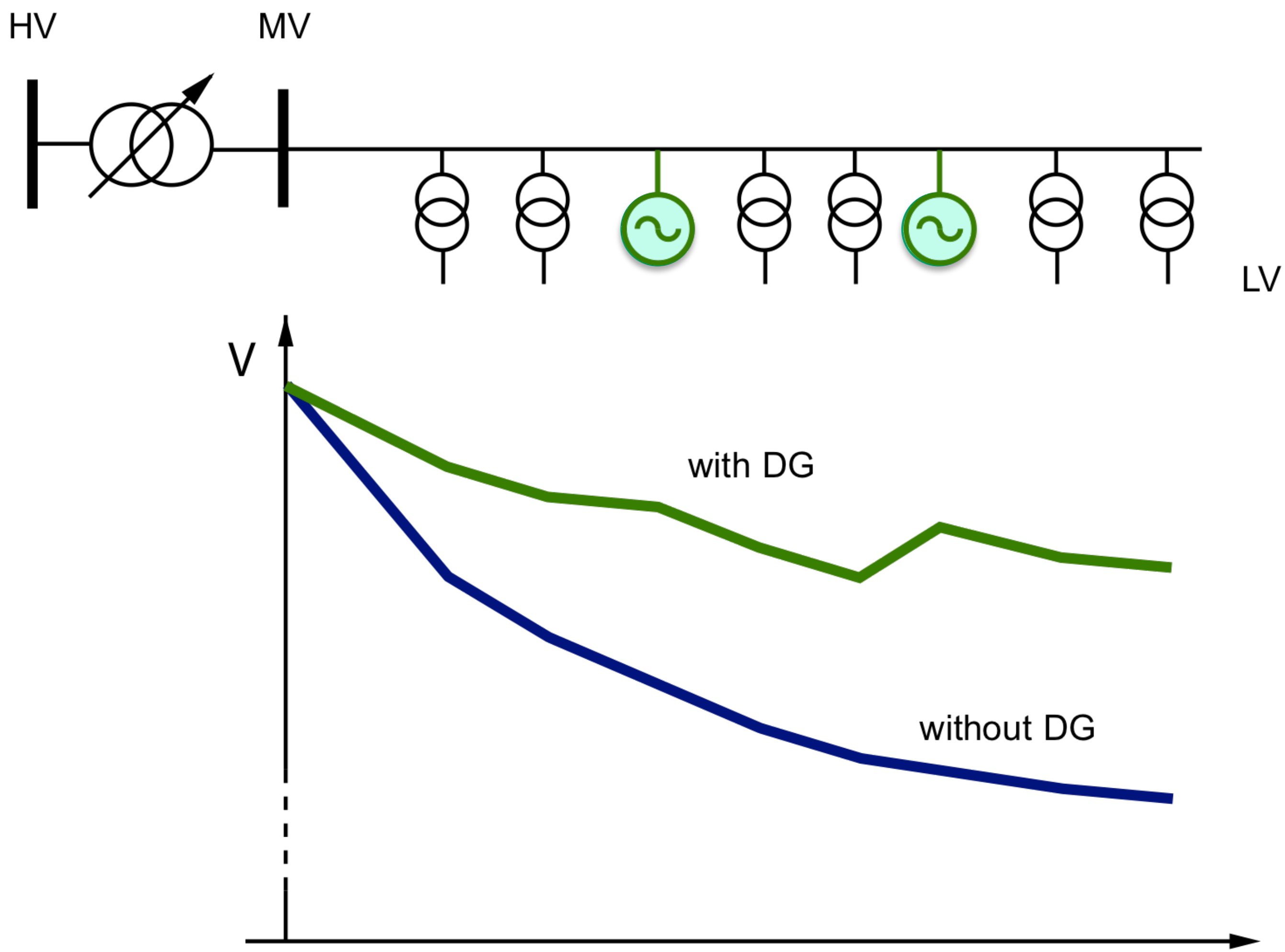
Distributed generation (DG)



Distributed generation (DG)

- Motivation for DG
  - Use renewable energy sources (RES) ⇒ **reduction of CO_2**
  - **Energy efficiency**; e.g., Combined Heat and Power (CHP)
  - Generation close to loads
  - Deregulation: Open access to distribution network
  - Subsidies for RES
  - …
- Technologies
  - Wind turbines
  - Photovoltaic systems
  - CHP (based on fossil fuels or RES)
  - Hydropower
  - Biomass
  - …

Technical impact of DG?



Wind turbines

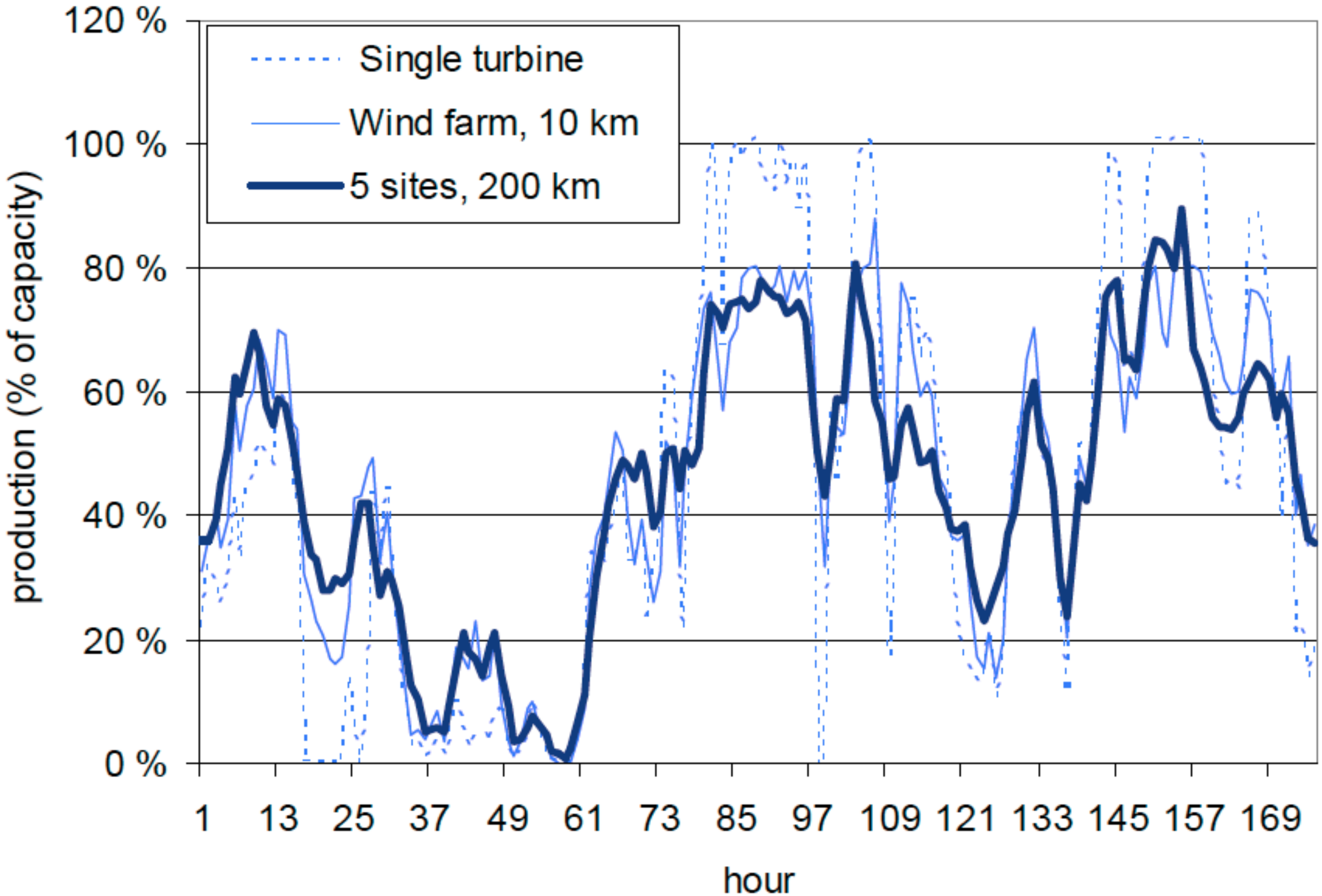
- Horizontal axis
  - <u>Upwind</u> vs downwind
  - Needs to be pointed into the wind
  - High rotational speed (10-22 rpm)
  - Needs a lot of space (cf. 60-90m high; blades 20-40m)
- Vertical axis
  - Omnidirectional
  - No need to point to wind
  - Lower rotational speed
  - Can be closer together

E.g., http://www.inflow-fp7.eu/

Darrieus

Savonius

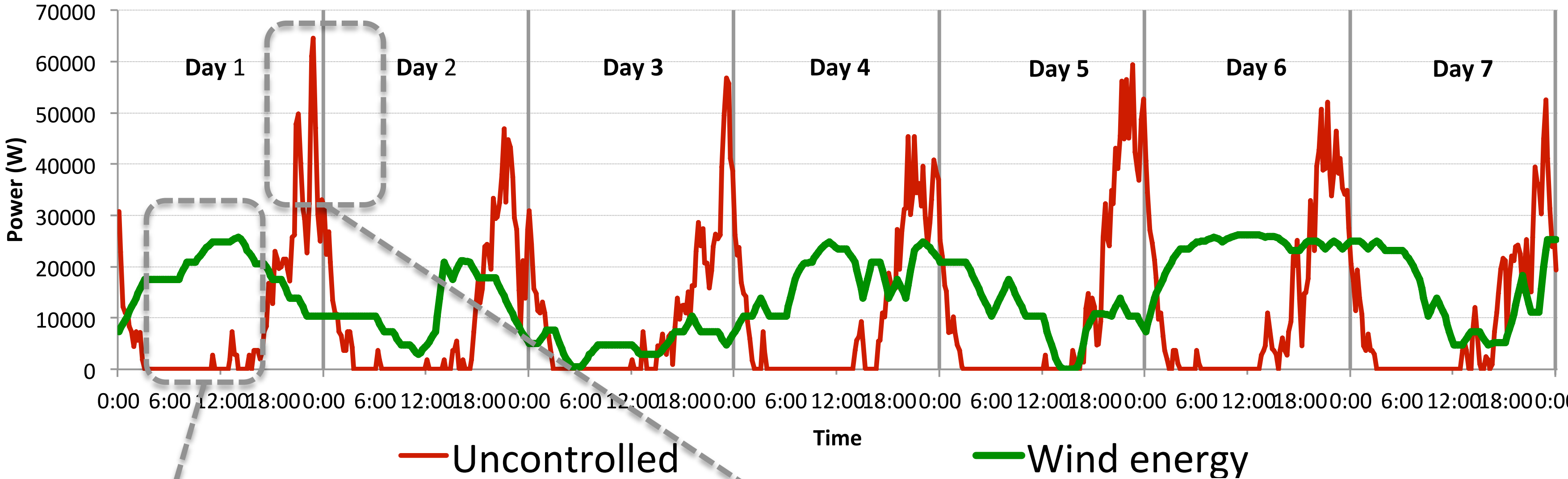
A typical wind profile



Case Study

*K. Mets, F. De Turck and C. Develder, **"Distributed smart charging of electric vehicles for balancing wind energy"**, in Proc. 3rd IEEE Int. Conf. Smart Grid Communications (SmartGridComm 2012), Tainan City, Taiwan, 5-8 Nov. 2012, pp. 133-138. doi:10.1109/SmartGridComm.2012.6485972*

Wind balancing with EV charging



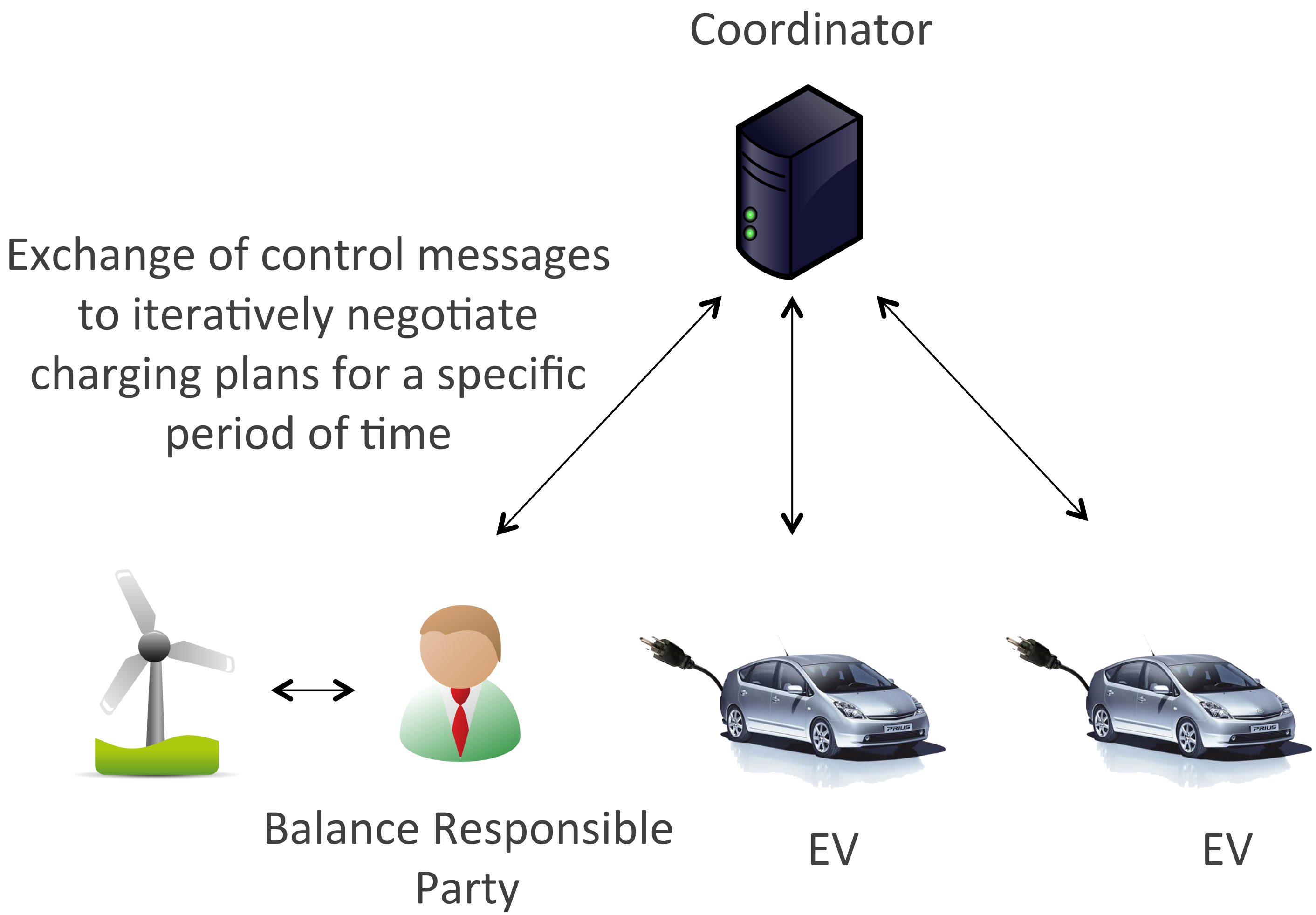
Supply/demand imbalance

- Inefficient use of RES
- Imbalance costs
- High peak loads

High peak loads

} Undesirable!

Distributed control



Electric vehicle model

- Minimize disutility:
  - Charging schedule variables: x_t^k = charging rate for **user *k*** at **time *t***
  - Spread demand over time, preferably at the "preferred charging rate" (p_k), which is the maximum supported charging rate in our case
  - Model behavior/preferences of the subscriber (β_k)

$$D_t^k\left(x_t^k\right) = \beta_k^t \cdot \left(p^k - x_t^k\right)^2 \qquad (1)$$

  - Charging schedule for a window of T time slots: Minimize disutility

$$\sum_{t=1}^{T} D_t^k\left(x_t^k\right) \qquad (2)$$

- Respect energy Requirement: $$\sum_{t=1}^{T_k} x_t^k = E_k \qquad (3)$$
  - Vehicle can only be charged between arrival time S_k and departure time T_k

Balance Responsible Party (BRP) Model

- Imbalance Costs
  - Minimize imbalance costs: Penalty cost if supply ≠ demand
  - Supply: Wind energy (w_t)
  - Demand: Total of all electric vehicles (d_t)
  - Tuning parameter: α
  - Cost function: $C_t\left(d_t\right) = \alpha \cdot \left(w_t - d_t\right)^2$
- For a planning window of T time slots, minimize: $\sum_{t=1}^{T} C\left(d_t\right)$

Centralized Optimization Model

- Based on social welfare maximization
  - Minimize imbalance costs *C*
  - Minimize user disutility *D*
- Objective:

$$\min_{d_t, x_t} \sum_{t=1}^{T} C(d_t) + \sum_{k=1}^{K} \sum_{t=1}^{T} D_t^k(x_t^k)$$

- Global constraints:

$$d_t = \sum_{k=1}^{K} x_t^k, \forall t \in \{1, 2, .., T\}$$

- Local constraints:
  - BRP: supply < limit
  - EV: energy & time constraints

Drawbacks:

1) Privacy: sharing of cost & disutility functions, arrival/departure info, …

2) Scalability

Distributed optimization model

- Move demand-supply constraint into objective, w/ Lagrange multiplier λ_t

$$\underbrace{\sum_{t=1}^{T} C(d_t) + \sum_{k=1}^{K}\sum_{t=1}^{T}\left(D_t^k\left(x_t^k\right)\right.}_{\text{original objective}} + \underbrace{\left.\lambda_t\left(x_k^t - d_t\right)\right)}_{\text{constraint}}$$

original objective *constraint*

- Notice: Objective function is separable into K+1 problems that can be solved in parallel *(assuming λ_t are given)*

1 BRP problem

$$\boxed{\sum_{t=1}^{T}\left(C\left(d_t\right) - \lambda_t d_t\right)} + \boxed{\sum_{k=1}^{K}\sum_{t=1}^{T}\left(D_t^k(x_t^k) + \lambda_t x_t^k\right)}$$

K subscriber problems

- Iteratively update pricing vector…

Distributed optimization model scheme:

1. Coordinator distributes virtual prices
2. BRP solves local problem
3. Subscribers solve local problem

} in parallel

4. Coordinator collects schedules:
   - **BRP**: $d^i = [d_1^i, d_2^i, ..., d_T^i]$
   - **EVs**: $x^{k,i} = [x_1^{k,i}, x_2^{k,i}, ..., x_T^{k,i}]$
5. Coordinator updates virtual prices:

$$\lambda_t^{i+1} = \lambda_t^i + \gamma \cdot \left[\sum_{k=1}^{K} x_t^{k,i} - d_t^i \right]$$

6. Repeat until demand = supply

Case study: Assumptions

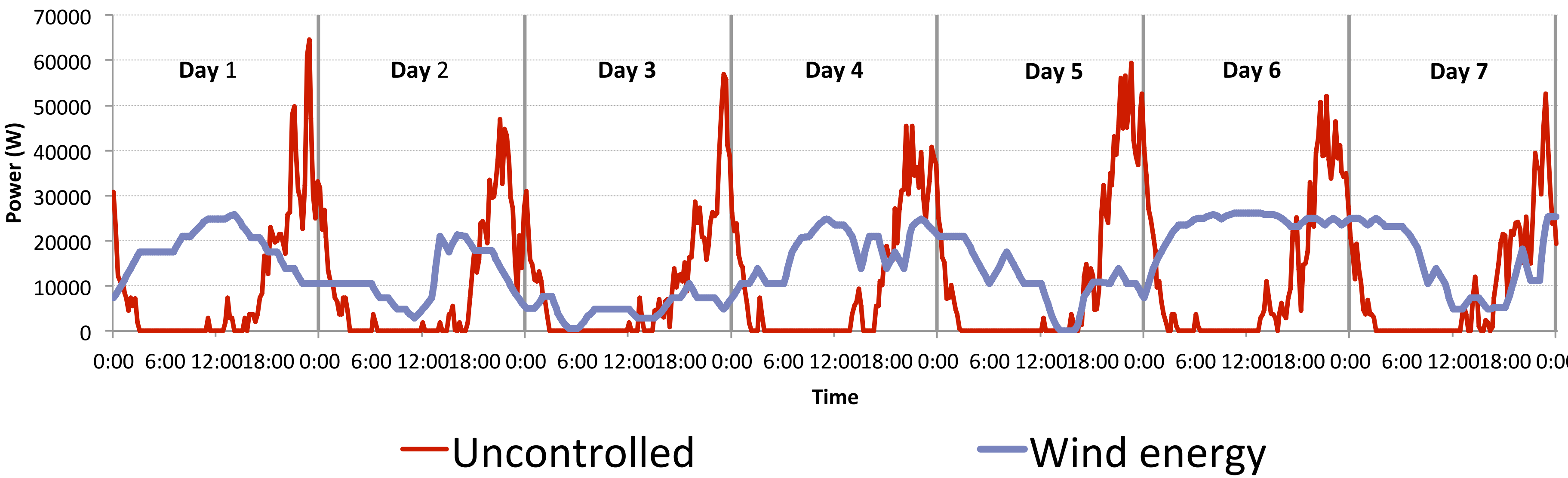
- Wind energy supply ≈ EV energy consumption
  - Energy supply = 6.8 MWh
- 100 Electric vehicles
  - Battery capacity: 10 kWh battery
  - Maximum charge power: 3.68 kW
  - Arrivals & departures: statistical model
  - Charging at home scenario
- Time
  - Simulate 4 weeks
  - Time slots of 15 minutes
  - Planning window of 24 hours

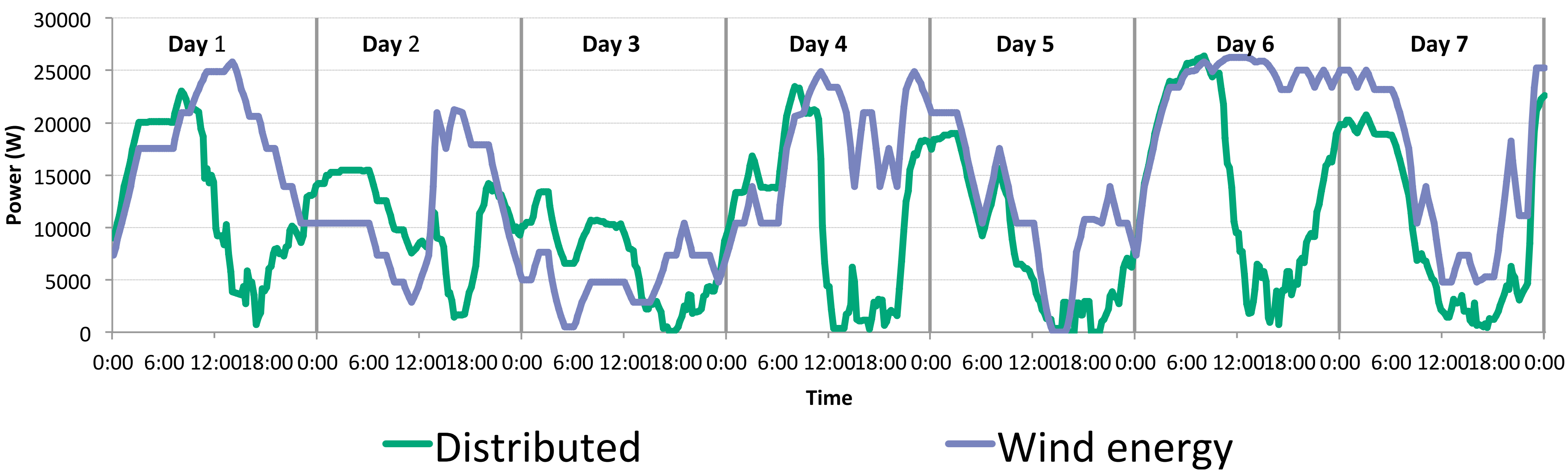
Case study: Algorithms

- **Uncontrolled business as usual (BAU)**
  - EV starts charging upon arrival
  - EV stops charging when state-of-charge is 100%
  - No control or coordination
- **Distributed algorithm**
  - Executed at the start of each time slot
- **"Ideal world" benchmark**
  - Offline all-knowing algorithm determines schedules for ALL sessions
  - No EV disutility function → maximum flexibility
  - Objective:

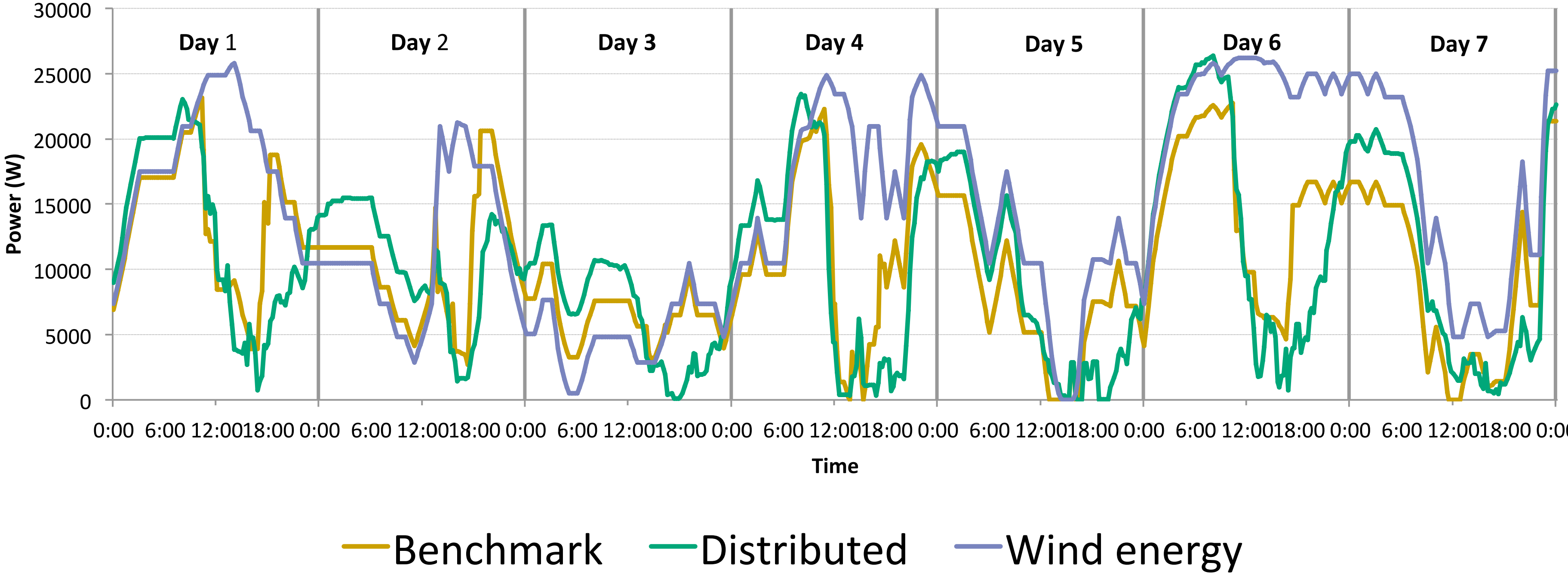
$$\min \sum_{t=1}^{S} \left(w_t - \sum_{k=1}^{K} x_t^k \right)^2$$

Results: Uncontrolled BAU vs. Distributed

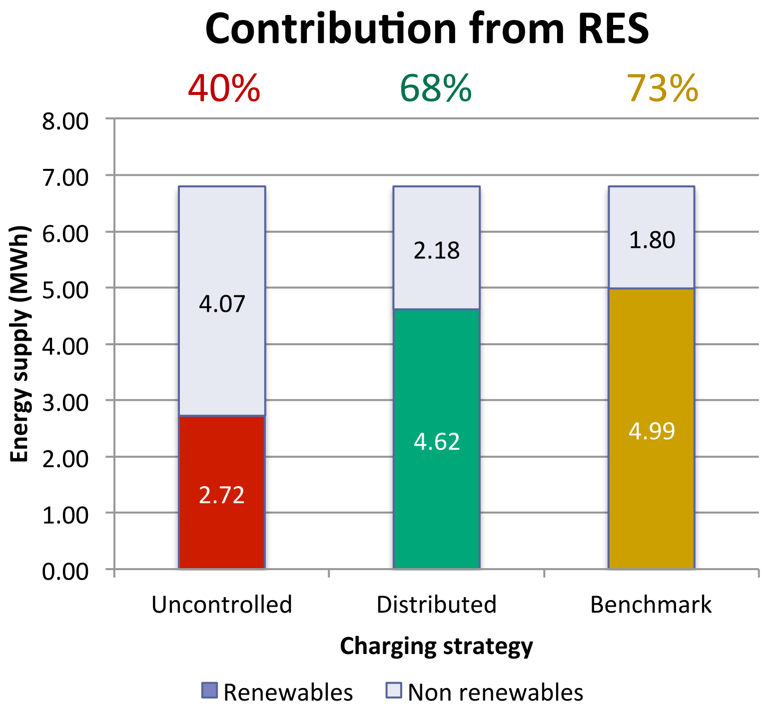


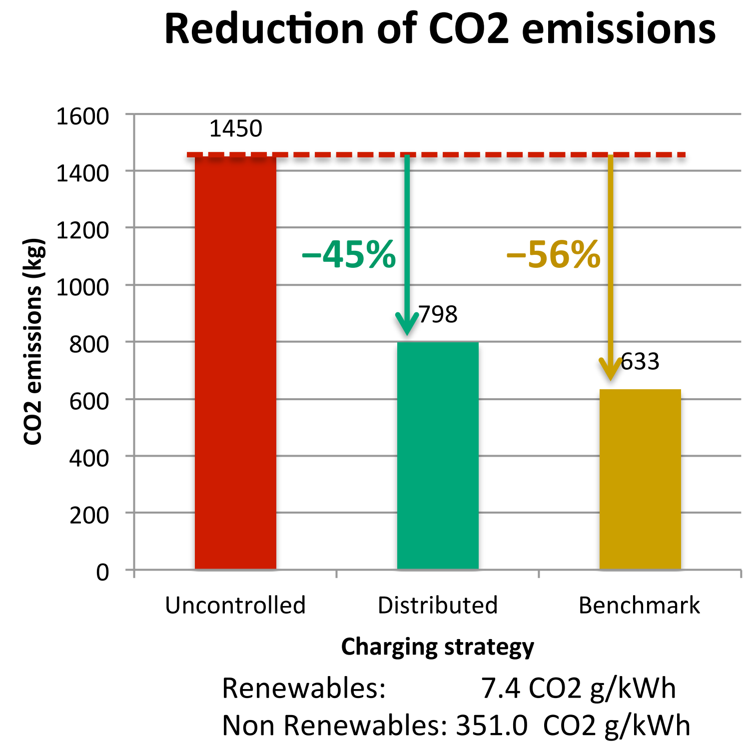


Results: Distributed vs. Benchmark



Results: Energy Mix





- Total energy consumption ≈ 6.8 MWh
- Substantial increase in the use of renewable energy
- Reduced CO_2 emissions

Conclusions

- **Objective**: balance wind energy supply with electric vehicle charging demand
- **Method**: Distributed coordination algorithm where participants exchange virtual prices and energy schedules
- **Performance**: Distributed coordination significantly better than BAU, close to “ideal world” benchmark
  - Increased usage of renewable energy sources
  - Reduction of CO_2 emissions

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*K. Mets, J. Aparicio and C. Develder, **"Combining power and communication network simulation for cost-effective smart grid analysis"**, IEEE Commun. Surveys Tutorials, Vol. PP, 2014, pp. 1-26. doi:10.1109/SURV.2014.021414.00116*

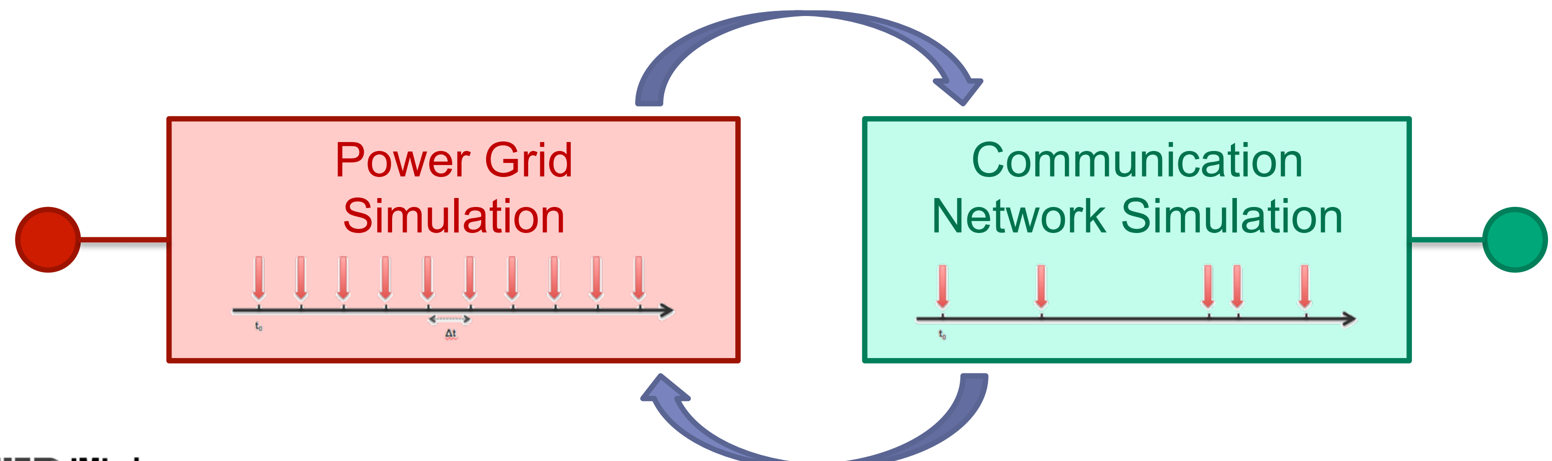
Problem Statement

- Simulators are already used in the two domains:
  - **Communication** network engineering
  - **Power** engineering

ns-2 / ns-3 | OMNeT++ | …

OpenDSS | Matlab tools | …

- In a **co-simulation** approach, power & communication are loosely coupled
  - Requires careful synchronisation
  - Drawback: no integration of tools



Challenge for co-simulation: Synchronisation

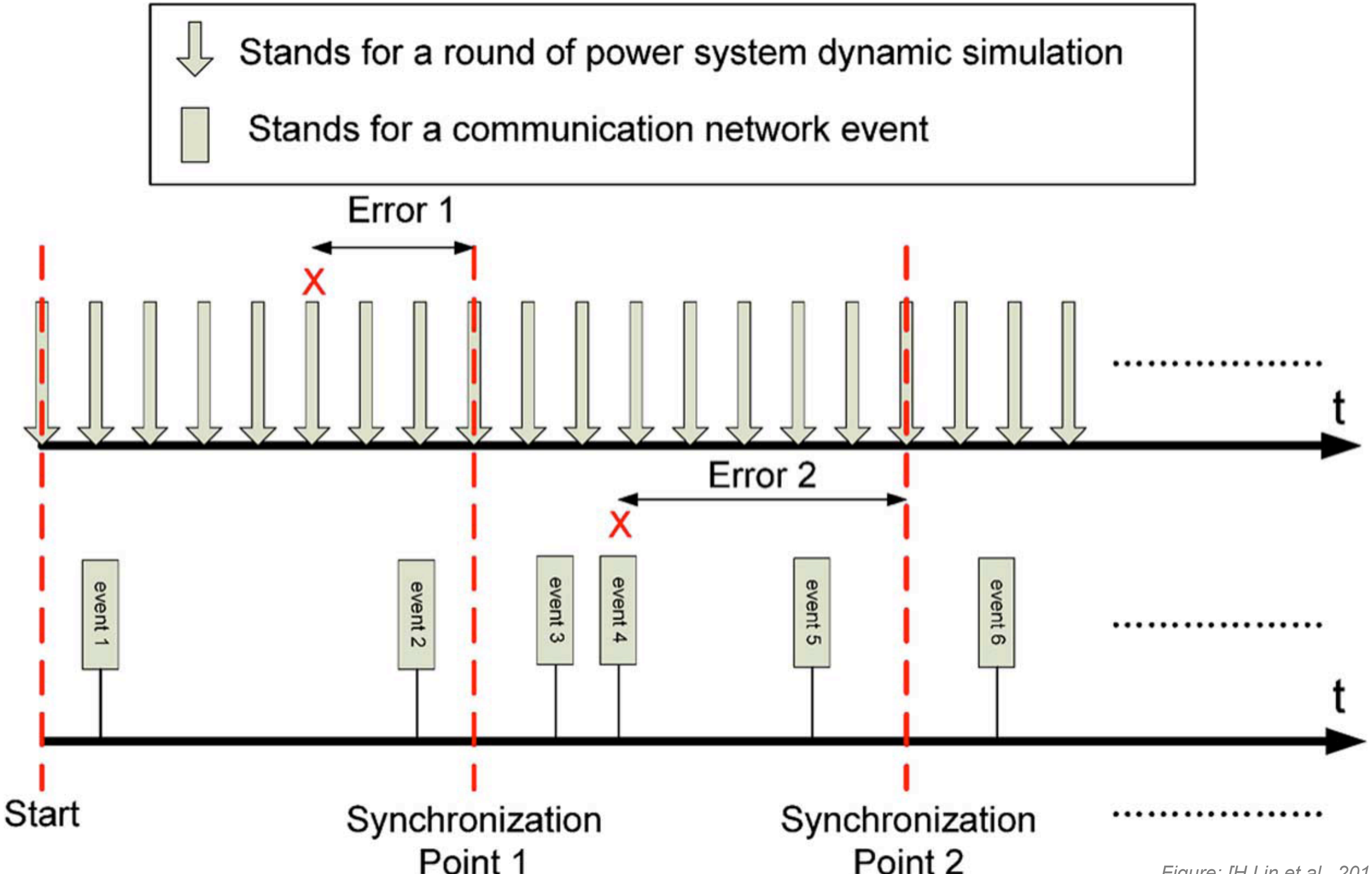
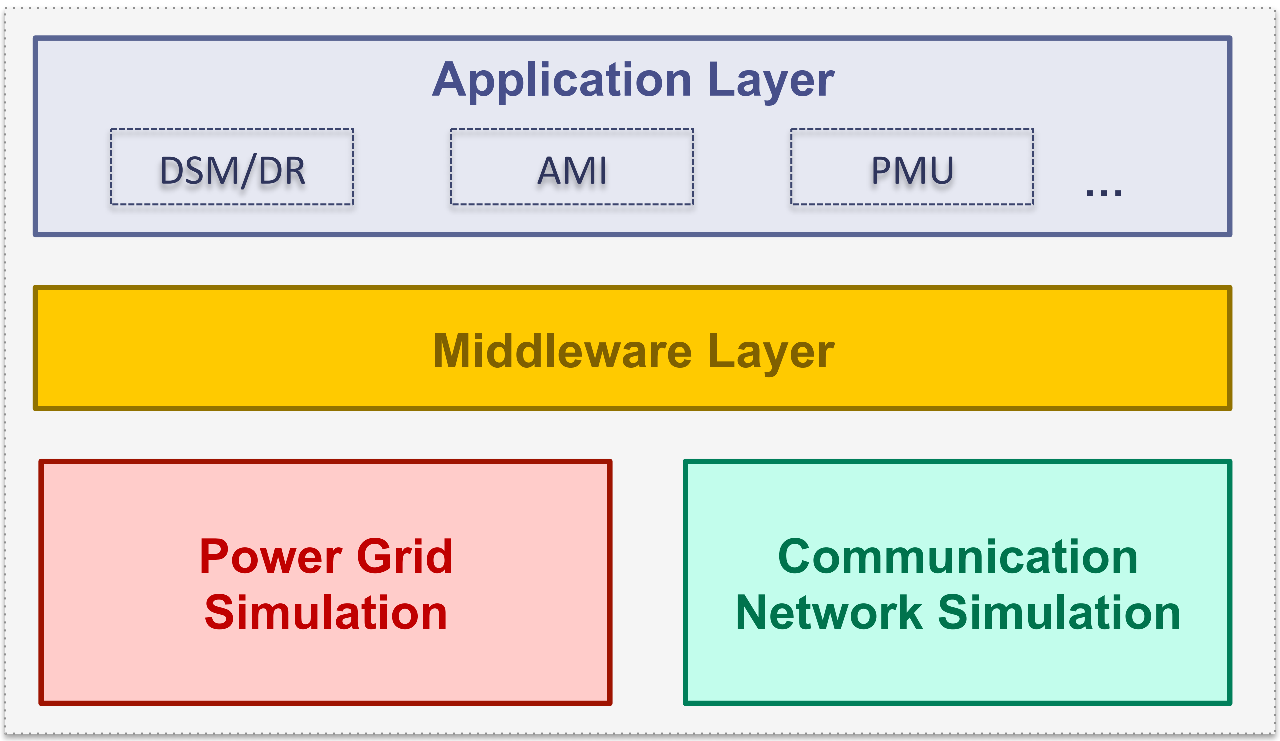


Figure: [H.Lin et al., 2012]

Our proposed solution

Integrated (combined) power grid and communication network simulation

→ Large scale smart grid simulations



Outline

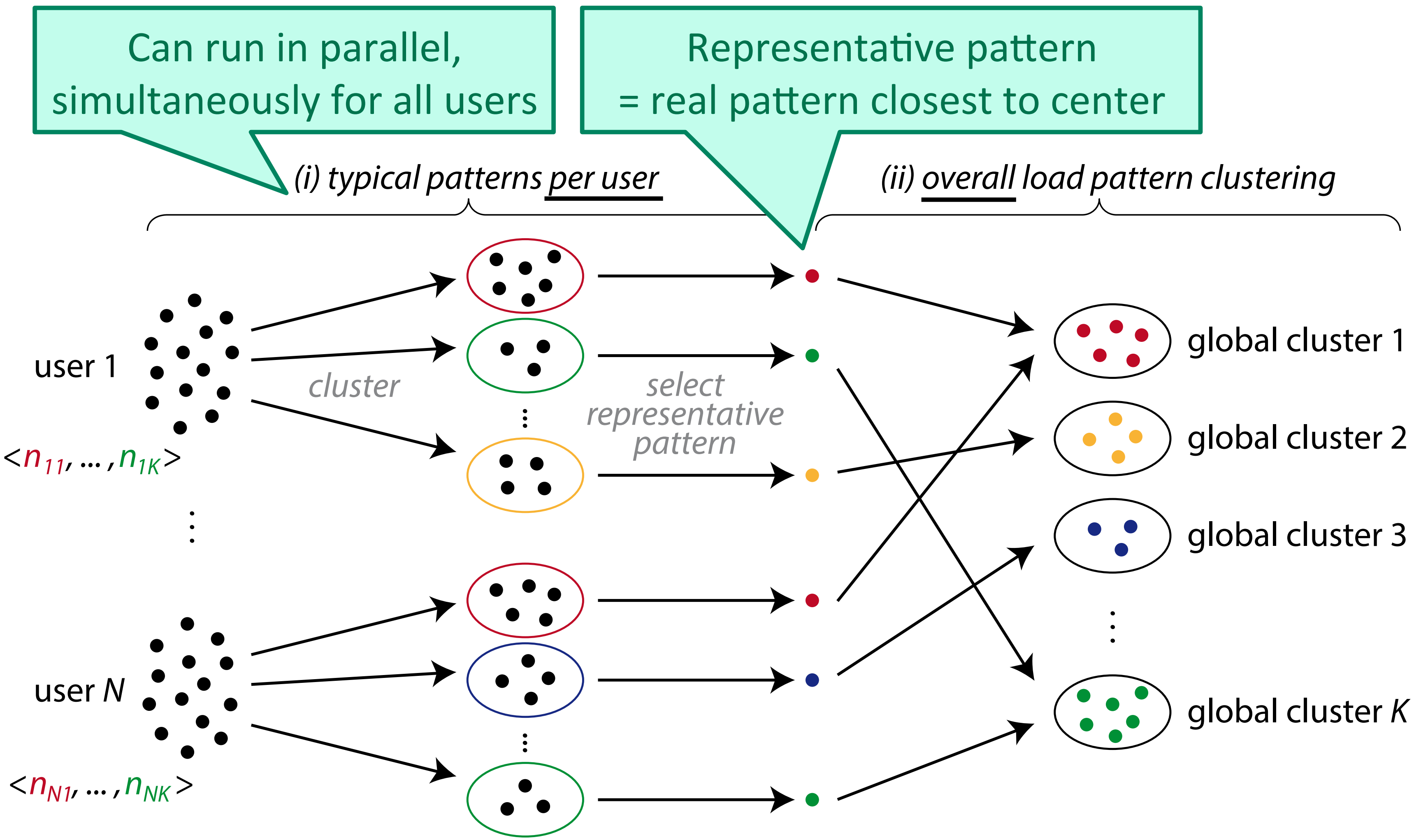
*K. Mets, F. Depuydt. and C. Develder, **"Two-stage load pattern clustering using fast wavelet transformation"**, IEEE Trans. Smart Grid, 2015, to appear*

Clustering smart metering data

- **Goal:** Identify different types of daily power consumption time series
  1. Single household: distinct types of daily load patterns?
  2. Over whole population: distinct groups of users?

- **Why?**
  - Demand analysis (nation-wide, distribution substations, … single houses)
  - Customer segmentation, tariffs, billing…
  - Power system planning
  - Load forecasting
  - Demand response programs
  - …

Two-stage load pattern clustering



Core ideas

- Hierarchical scheme
- Wavelet transformation:
  - Dimensionality reduction
  - Invariance/tolerance to time shifting

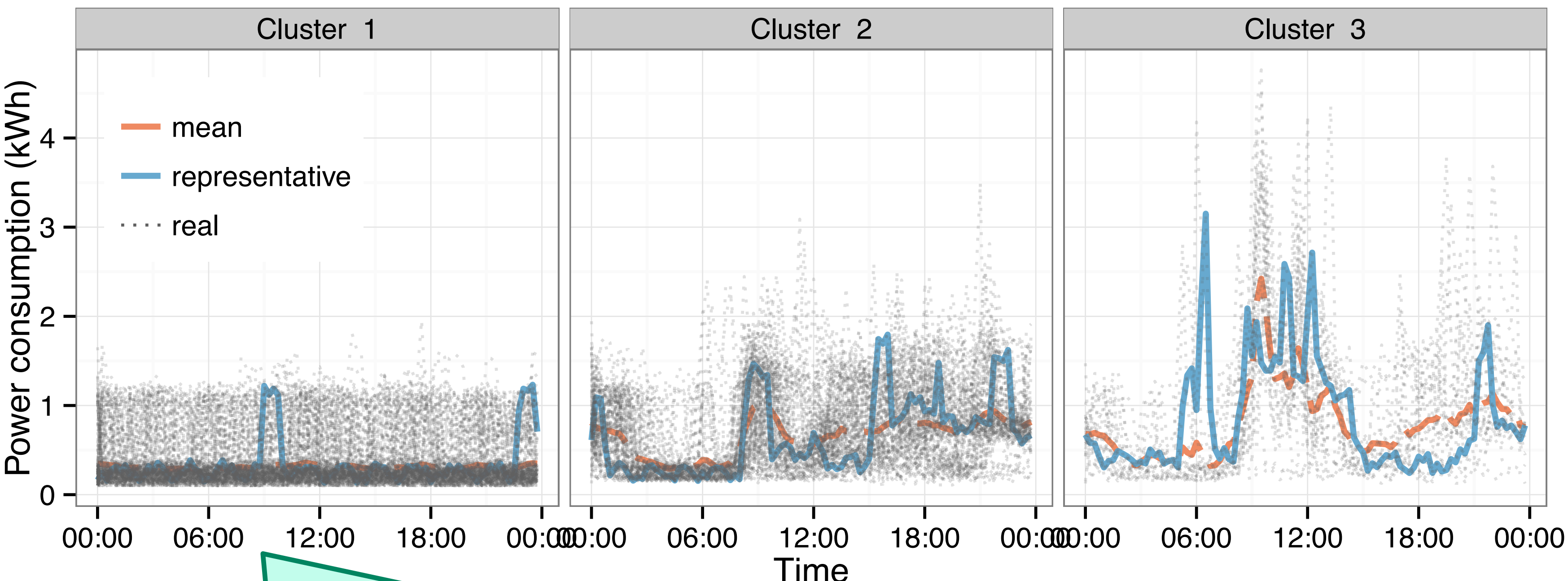
- G-means (instead of k-means) [Hamerly2003]

G. Hamerly, C. Elkan, "Learning the k in k-means", NIPS 2003

Sample result: Single user

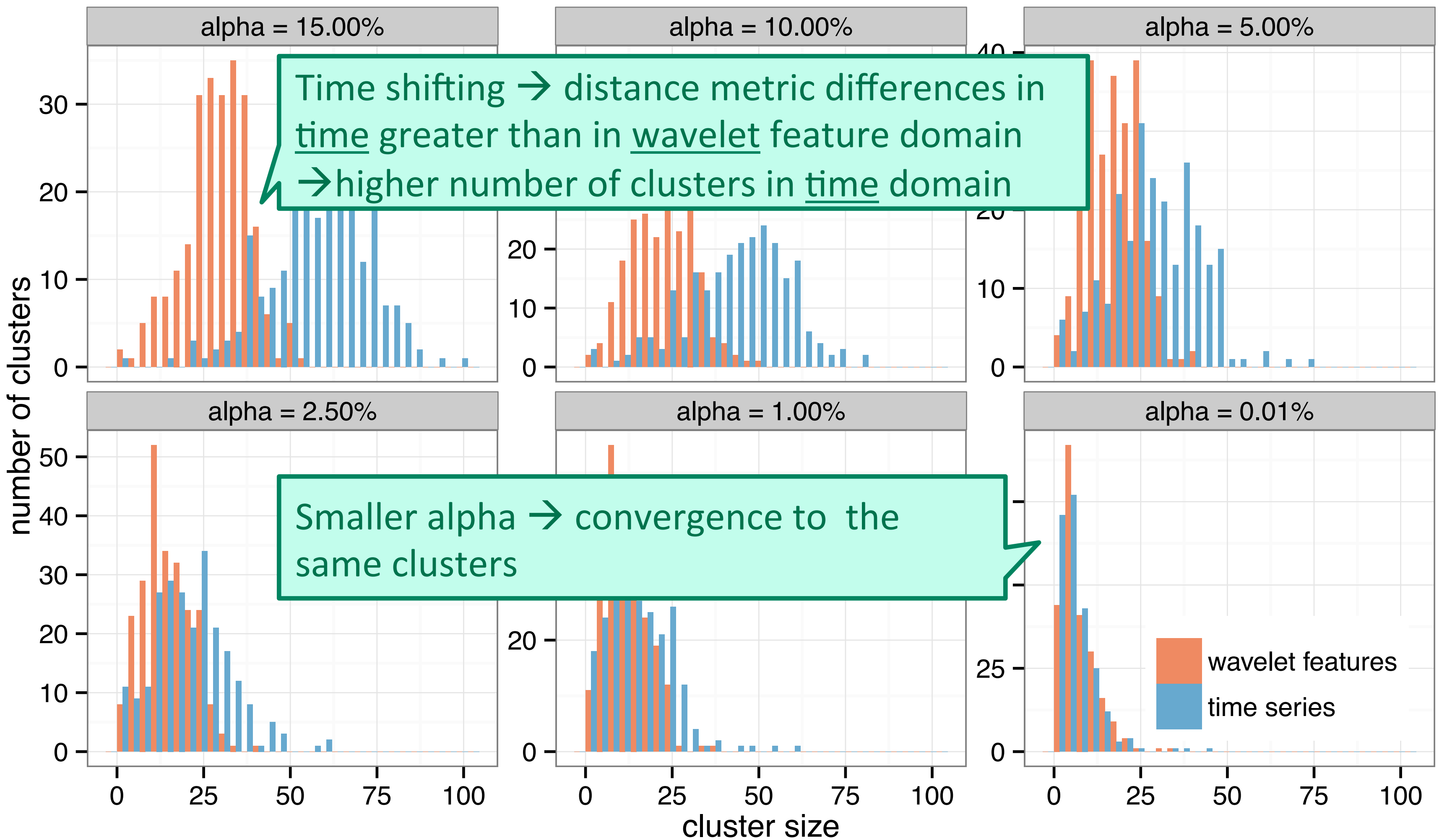
For alpha = 0.01% → low number of clusters

Note: representative ≠ arithmetic mean



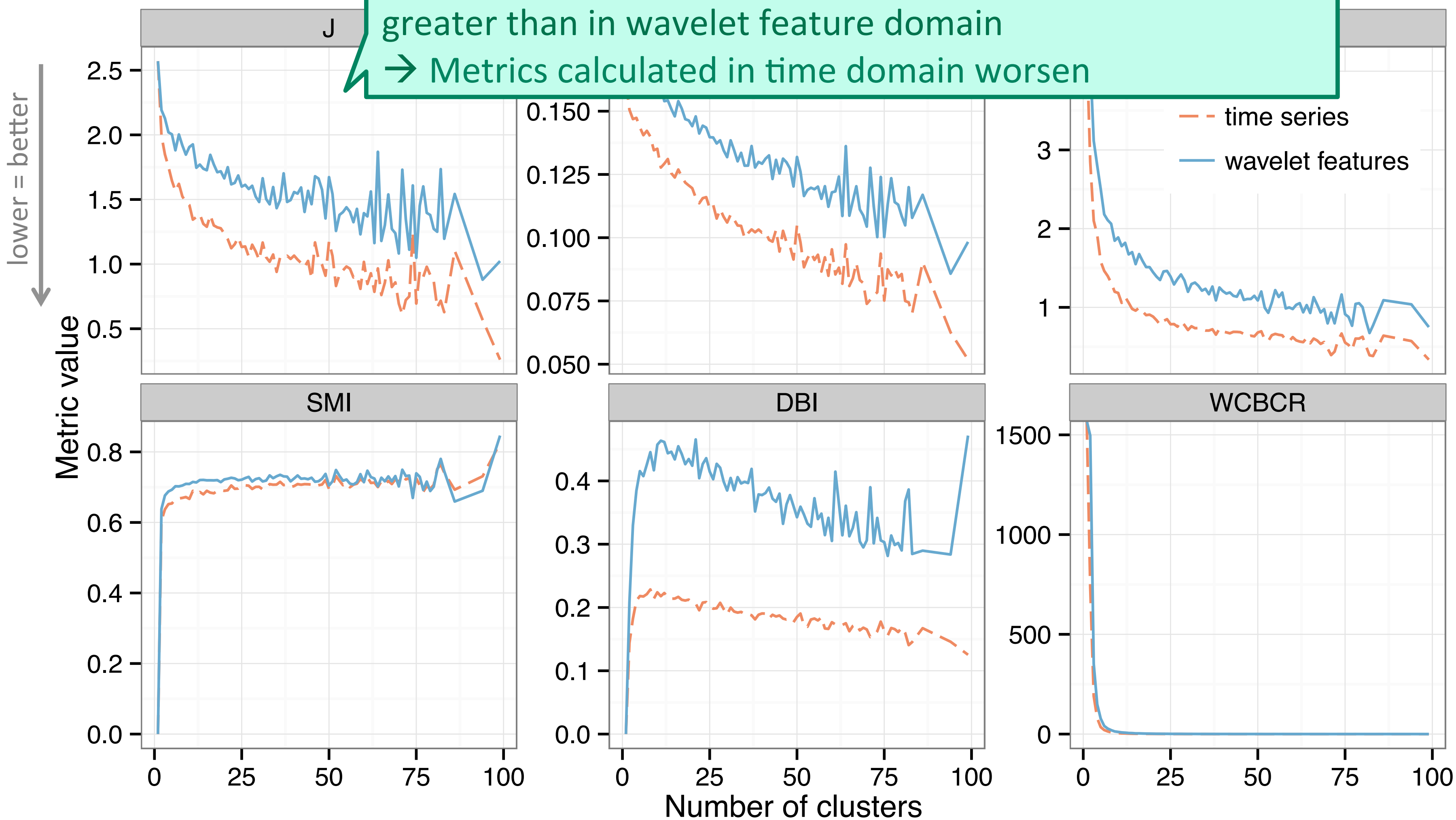
Because of FWT: similar time shifted patterns are clustered together!

Time vs wavelet domain: Number of clusters



Time vs wavelet domain: Cluster quality (in time domain)

Time shifting: distance metric differences in time domain greater than in wavelet feature domain
→ Metrics calculated in time domain worsen



Conclusions

- Totally unsupervised clustering process
  - No a priori definition of 'typical day', groupings into weekday/weekend …
  - Cluster quality does not suffer from dimensionality reduction
- Note on scalability:
  - Stage 1 = executed per user (in parallel)
  - Stage 2 = number of profiles to cluster is limited, by reducing 'representative' profile
  - Vector space dimensionality is reduced by FWT (96 → 7 or 8 features)

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Living Lab Electric Vehicles program

- Data from real life, operational EV usage/charging
- Vehicle types:
  - **Company car**: single employee to commute & private trips.
  - **Pool car**: trips during office hours
  - **Utility car**: for professional usage (e.g., deliveries, technicians)
  - **Private car**: individual family

- Goal: Identify **flexibility**
  = power we can consume extra / reduce, and for how long

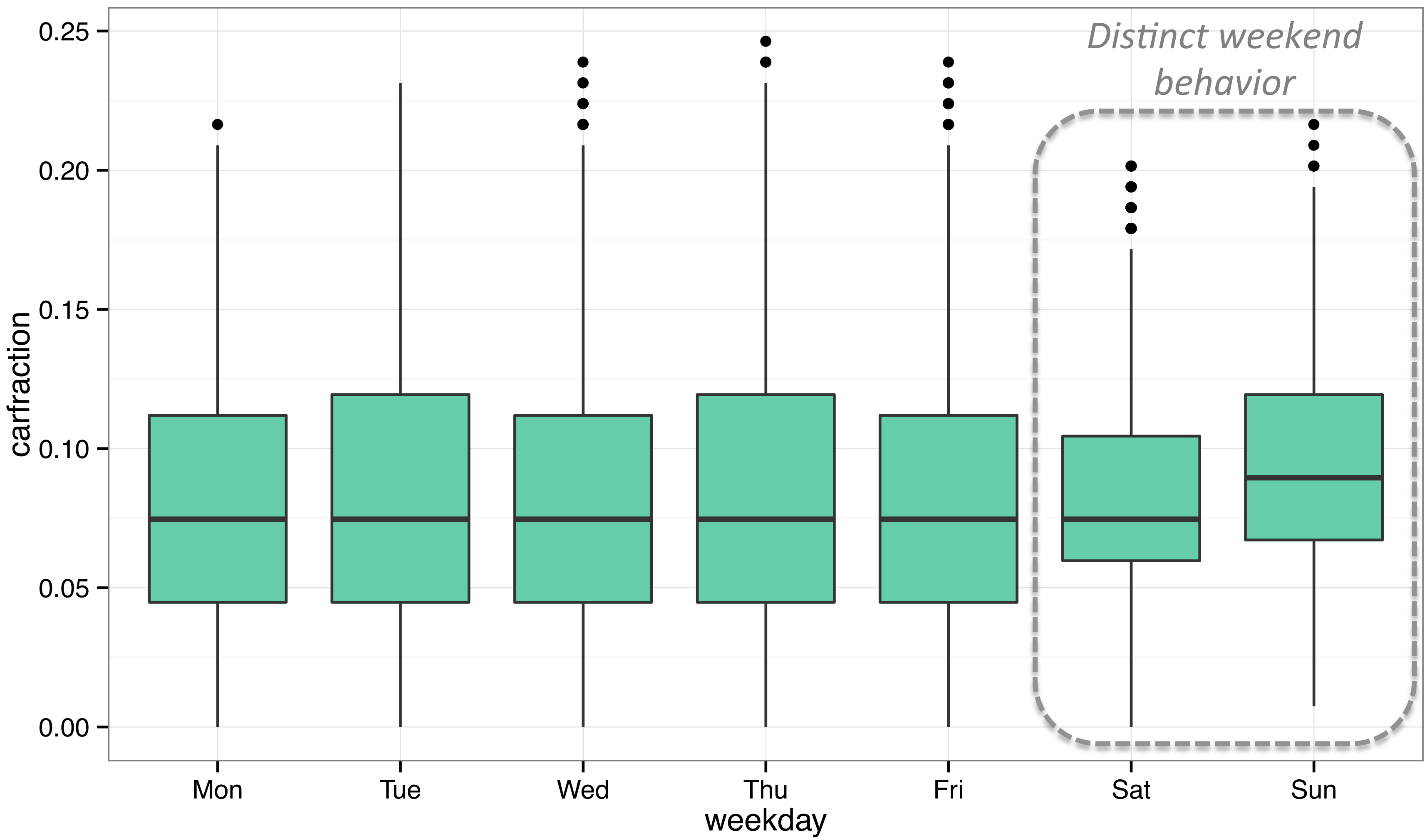
Q1: How many cars?

Q2: Time window to shift charging?

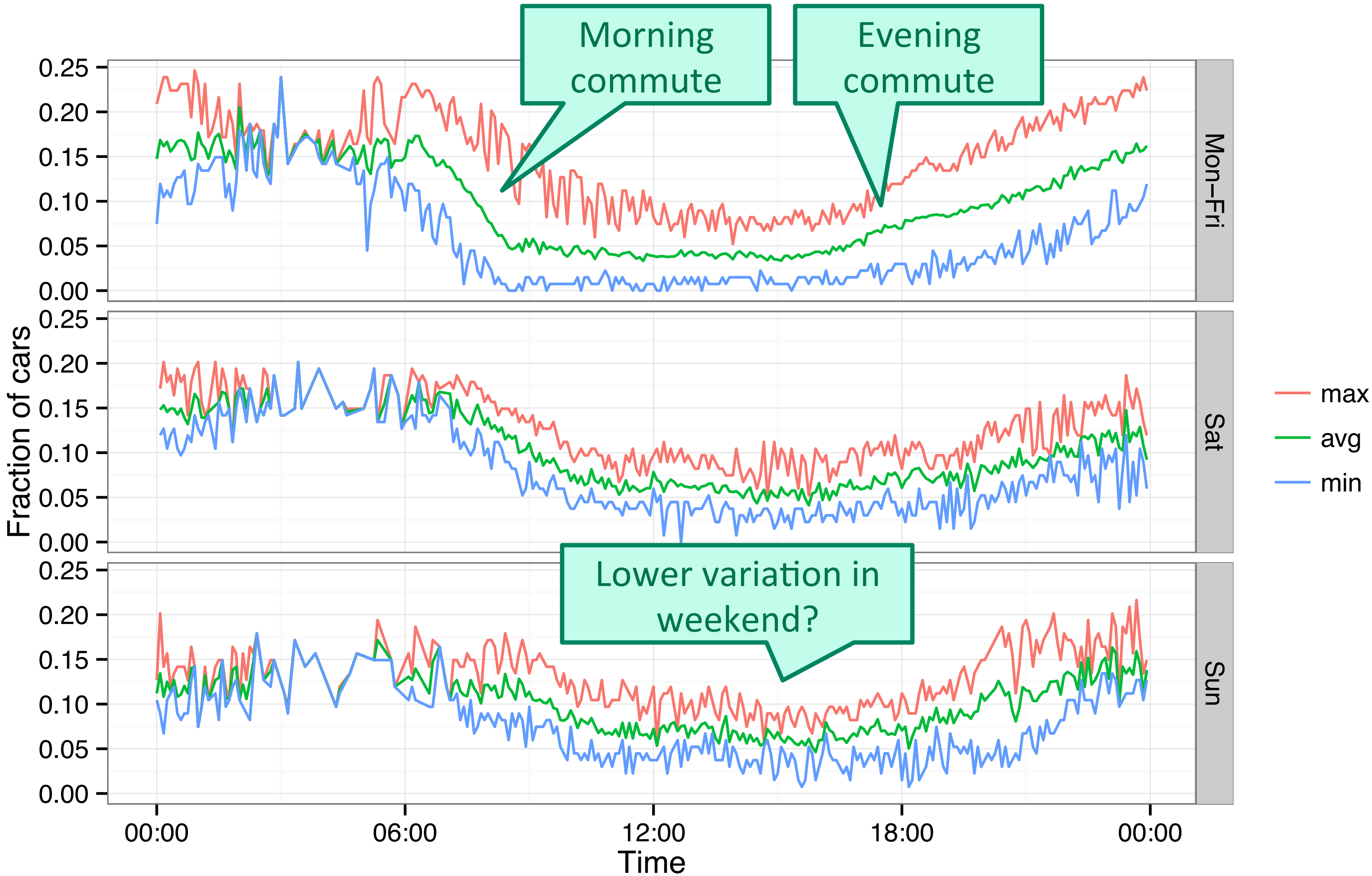
Flexibility analysis of private EV charging

# vehicle years	21.48 years
Total charged energy	72 439 kWh
Total charging session duration	77 170 h
Total effective charging time (3.68 kW charging rate)	19 684 h
# charging sessions	8521
Avg. daily charged energy	9.24 kWh
Avg. Charged energy per session	8.50 kWh
Avg. Number of sessions/day	1.09
Avg. Daily charging session duration	9.05 h
Avg. Daily effective charging time duration	2.31 h (= 25.5% of connection time)

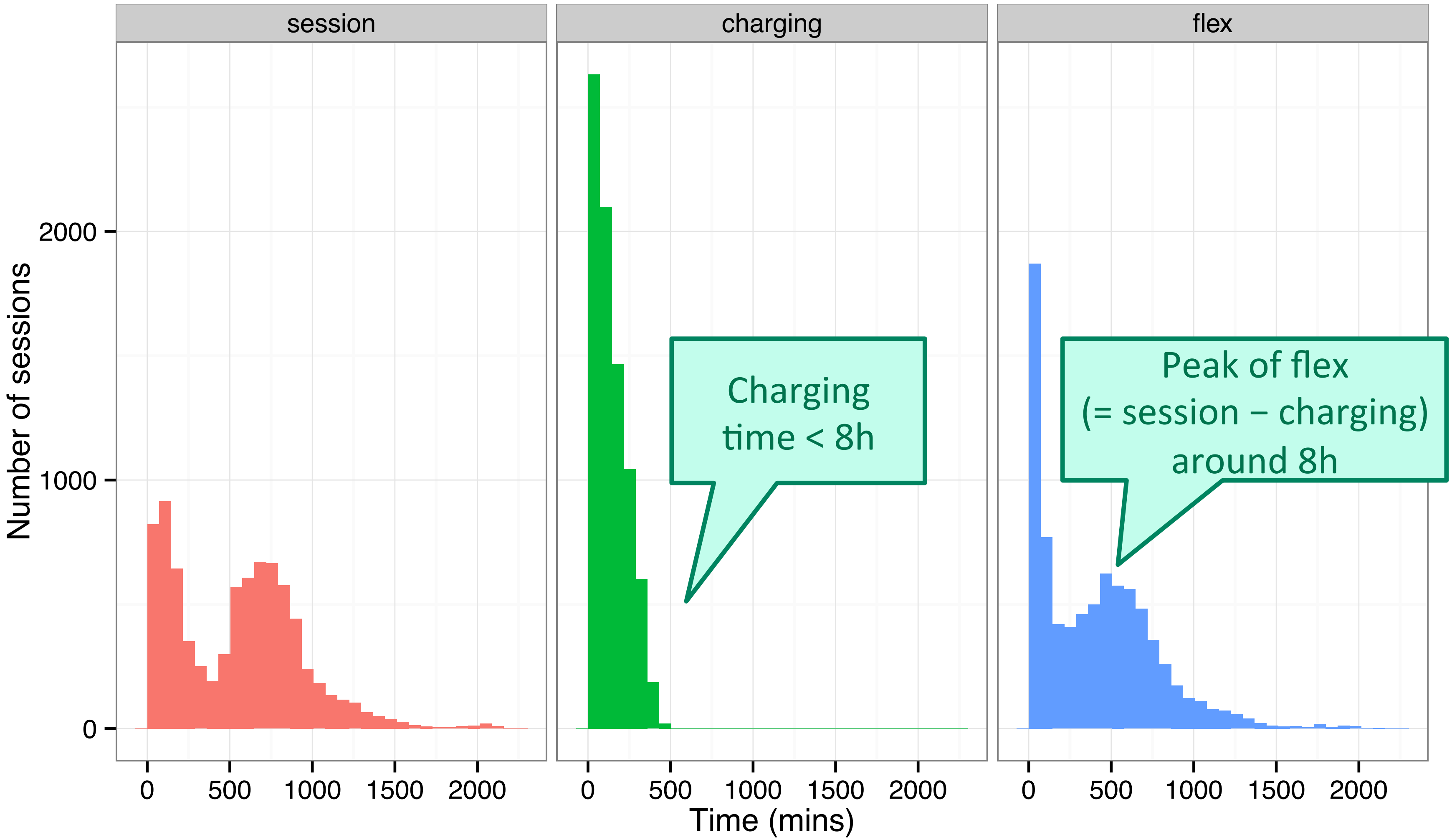
Q1: How many cars are connected?



Q1: How many cars are connected?



Q2: Time window for shifting?



Putting it together: Bounds on flexibility from EVs

- $P_{ADD}(t, \Delta)$ = Maximal power that can be **added** in interval [t, t+Δ]:
  - Charging session has to include [t, t+Δ]
  - Charging duration ≥ Δ

Upper bound on **extra** power vs no Evs in [t,t+Δ]

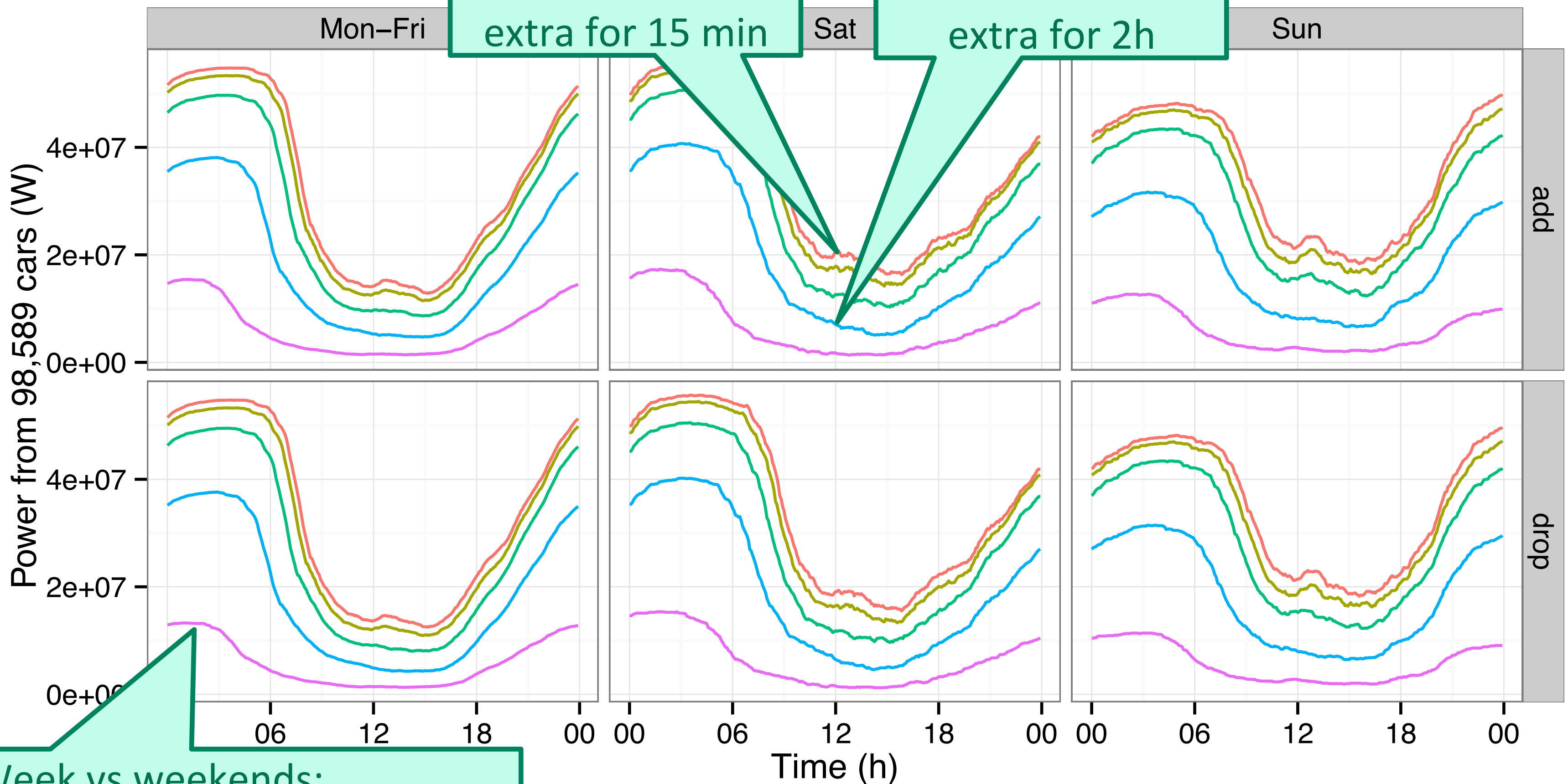
Upper bound on power **reduction** vs maximal EV charging in [t,t+Δ]

- $P_{DROP}(t, \Delta)$ = Maximal power that can be **dropped** in interval [t, t+Δ]
  - Charging session has to include [t, t+Δ]
  - Charging duration ≥ Δ [else it couldn't have been there in the first place]
  - Flexibility = session duration − Δ ≥ charging duration [we can move it away]

Putting it together: Bounds on flexibility from EVs

Saturday noon:
max. 20MW
extra for 15 min

Saturday noon:
max. ~7MW
extra for 2h



Week vs weekends:
- Higher flex at night
- Lower flex during the day

Conclusion on flexibility analysis EVs

- Real world data set
- Methodology to quantify flexibility

- Application? E.g., extrapolation to 3% of Flemish fleet by 2020:
  - ~100k cars out of ~3.2M
  - E.g., noon in weekend => can have ~7MW extra for 2h

Wrap-up

Summary

- Challenge: deal with renewable sources
- Demand response algorithms: initial feasibility studies
  - How close to "best" possible? scalable?
  - What are achievable benefits?
- Get insight in consumption/production: e.g., clustering as first step
- Quantify flexibility, e.g., the EV case study
- What's next?

  E.g., refine "disutility" from user; "imbalance" from business perspective; evaluate using real(istic) data…

  - Can we **learn/predict** flexibility, e.g., from smart metering data?
  - Can we infer **user behavior**, and from there (context-aware) preferences?
  - Evaluate **business case** of flexibility?
  - Convincingly demonstrate flexibility exploitation in the real world?

Thank you … any questions?

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