Introduction – Chris Develder

- Professor at Ghent University since Oct. 2007
  - *Research Interests*: **smart grids** (data analytics; optimization/scheduling algorithms for DSM/DR), **information 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 (IE)
- Industry Experience: network planning/design tools
  - OPNET Technologies (now part of Riverbed), 2004-05
- PhD, Ghent University, 2003
  - "Design and analysis of optical packet switching networks"
- More info: http://users.atlantis.ugent.be/cdvelder

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FACULTY OF ENGINEERING AND ARCHITECTURE

Algorithms and communications for smart grids: Knowing and controlling power consumption

Kevin Mets, Nasrin Sadeghianpourhamami, Matthias Strobbe, Chris Develder

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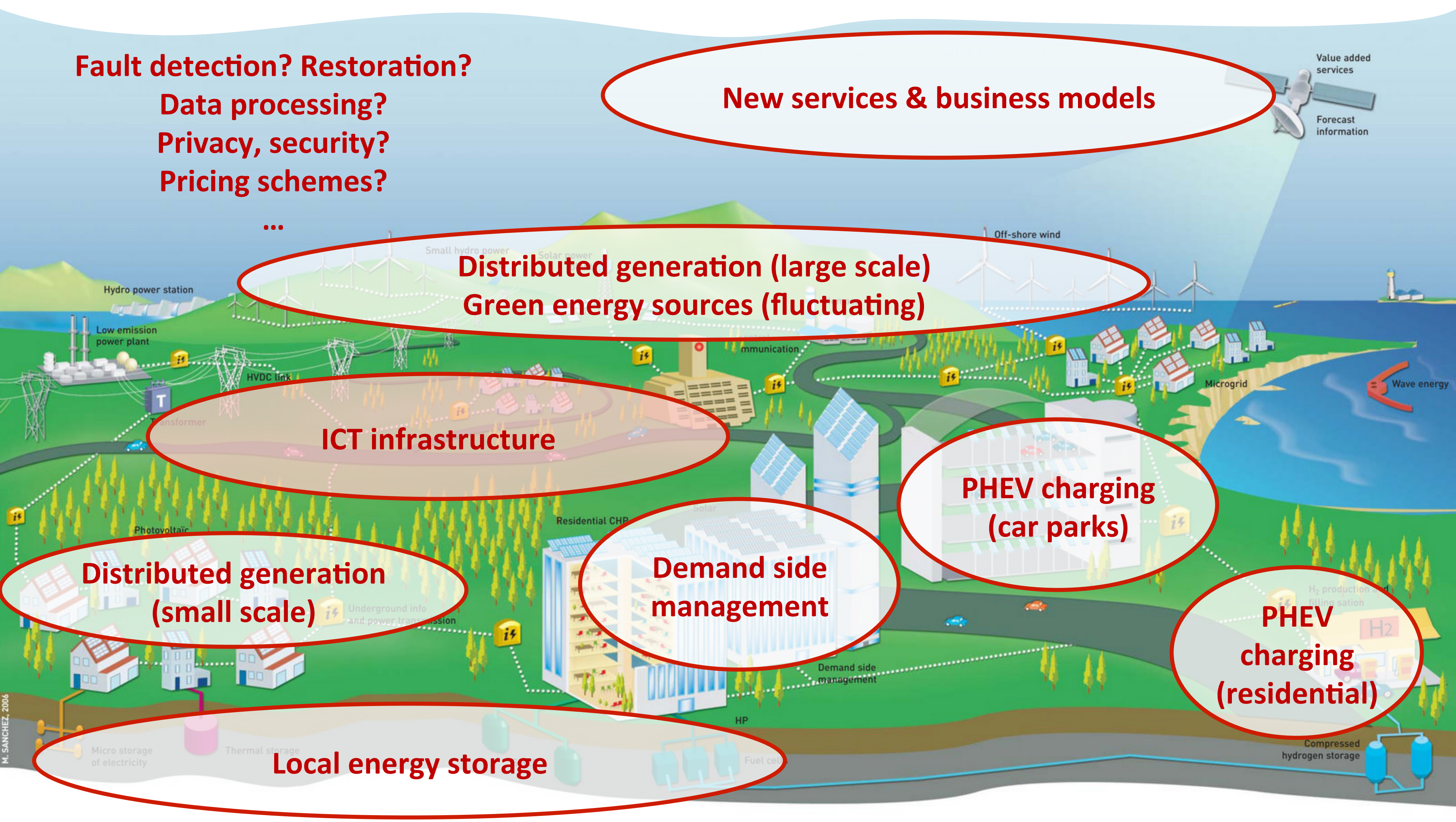
Dept. of Information Technology – IBCN

iMinds FUTURE INTERNET DEPT.

INTEC

Smart Grids

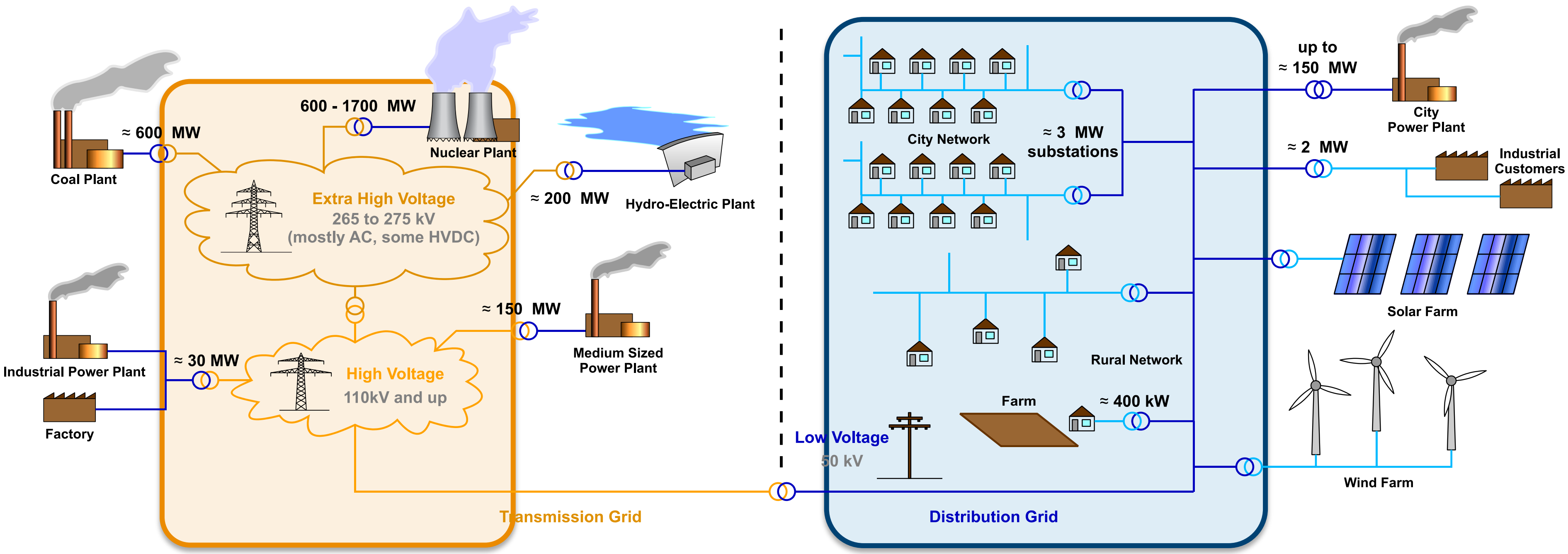


Fault detection? Restoration?
Data processing?
Privacy, security?
Pricing schemes?
...
New services & business models
Value added services
Forecast information
Distributed generation (large scale)
Green energy sources (fluctuating)
Hydro power station
Low emission power plant
Off-shore wind
HVDC link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

Power grid structure

Transmission network (operated by TSO)

Distribution network (operated by DSO)



C. Develder, et al., "Algorithms and comms for smart grids: Knowing and controlling power consumption", 10 Jun. 2016

Outline

1. Introduction

Part I: Algorithms for DSM/DR

2. Example 1: Peak shaving
3. Example 2: Wind balancing

Part II: Data analytics

5. Clustering smart metering data
6. EV usage analysis

Part III: Communication middleware

7. C-DAX: A cyber-secure data and control cloud for power grids

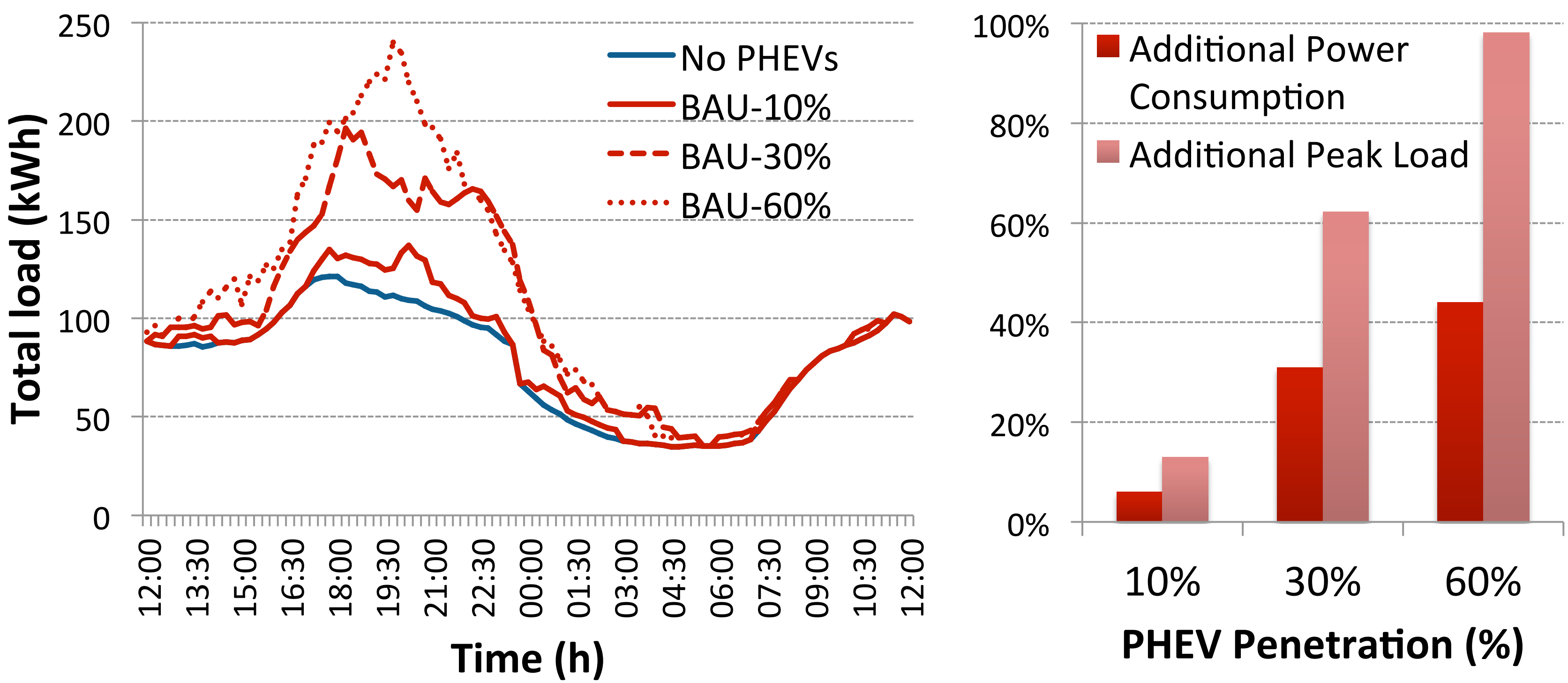
K. Mets, R. D'hulst and C. Develder, ***"Comparison of intelligent charging algorithms for electric vehicles to reduce peak load and demand variability in a distribution grid"****, J. Commun. Netw., Vol. 14, No. 6, Dec. 2012, pp. 672-681. doi:10.1109/JCN.2012.00033*

Example case study: EV charging

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

Impact of EV charging

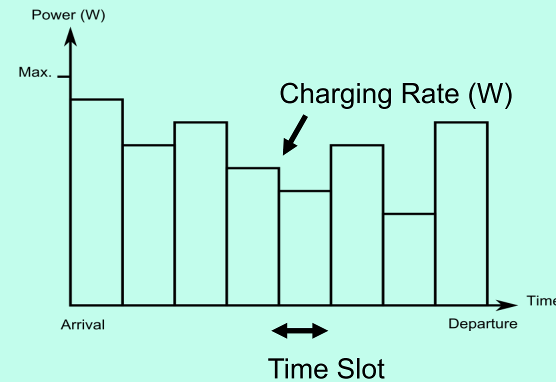
- Sample analysis for 150 homes, x% of them own a PHEV
- BAU = maximally charge upon arrival at home

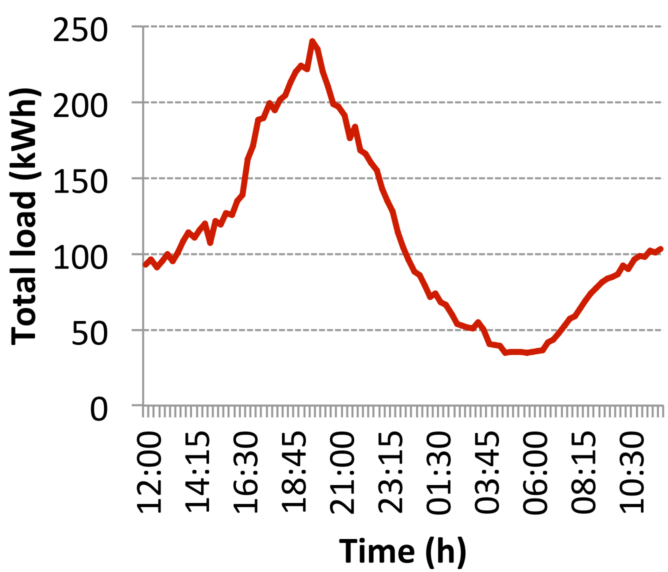


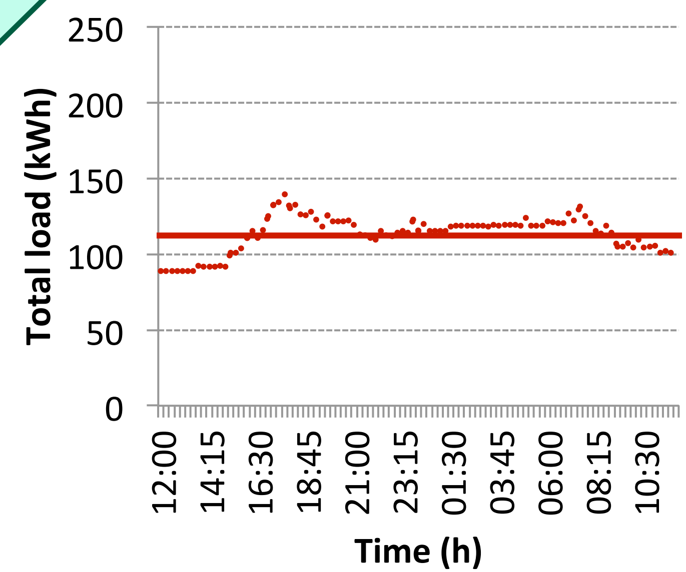
Controlling EV charging?

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

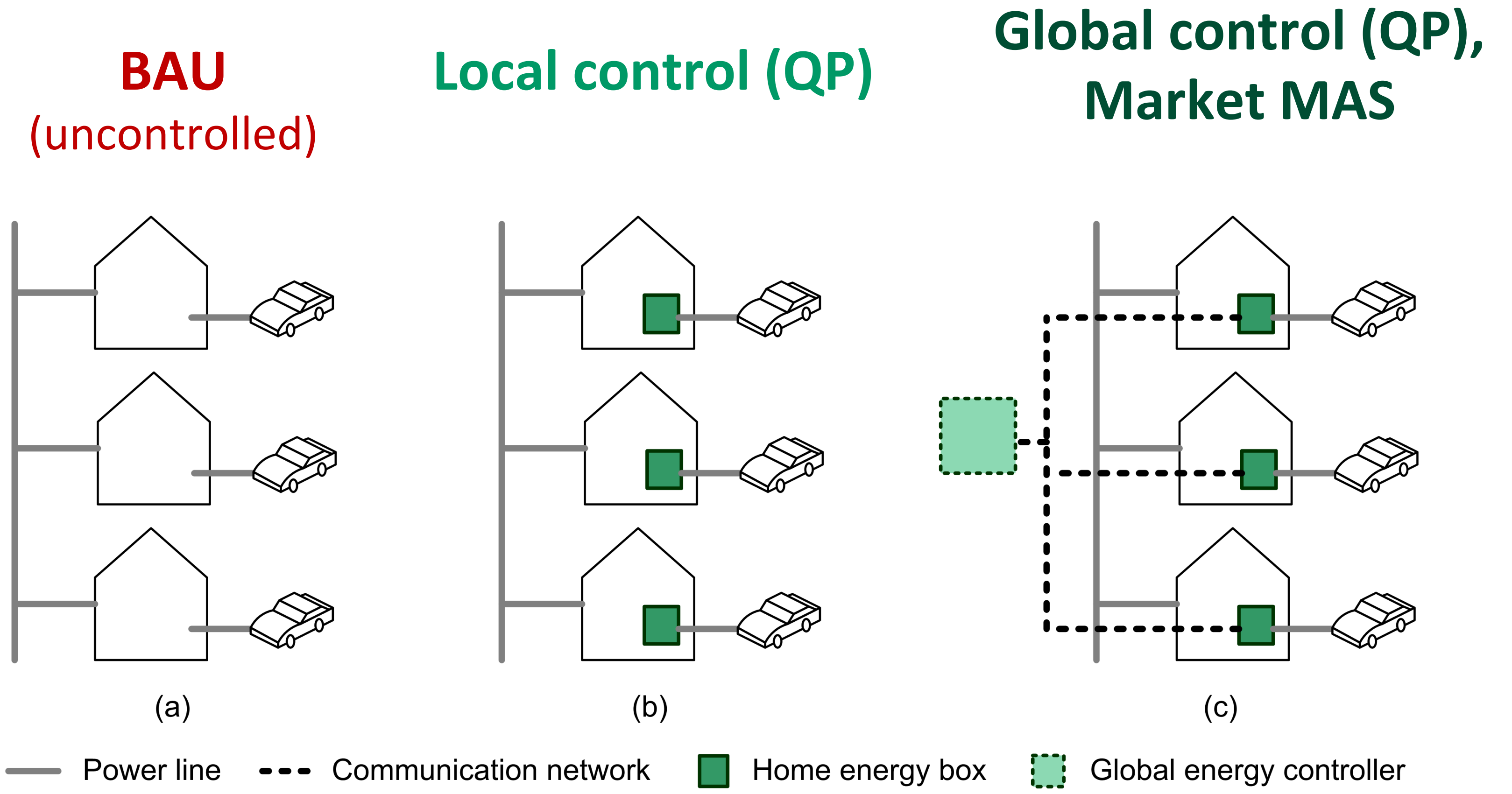
Charging schedule





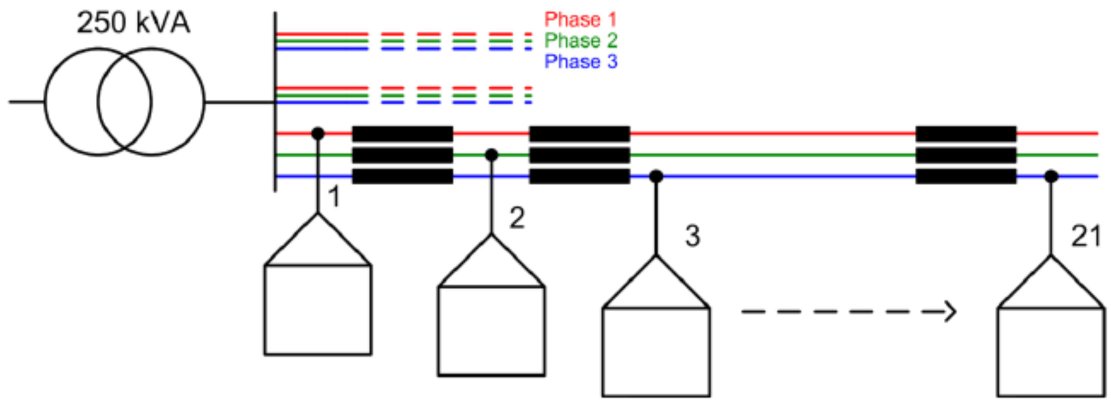


Smart charging: QP



Case study

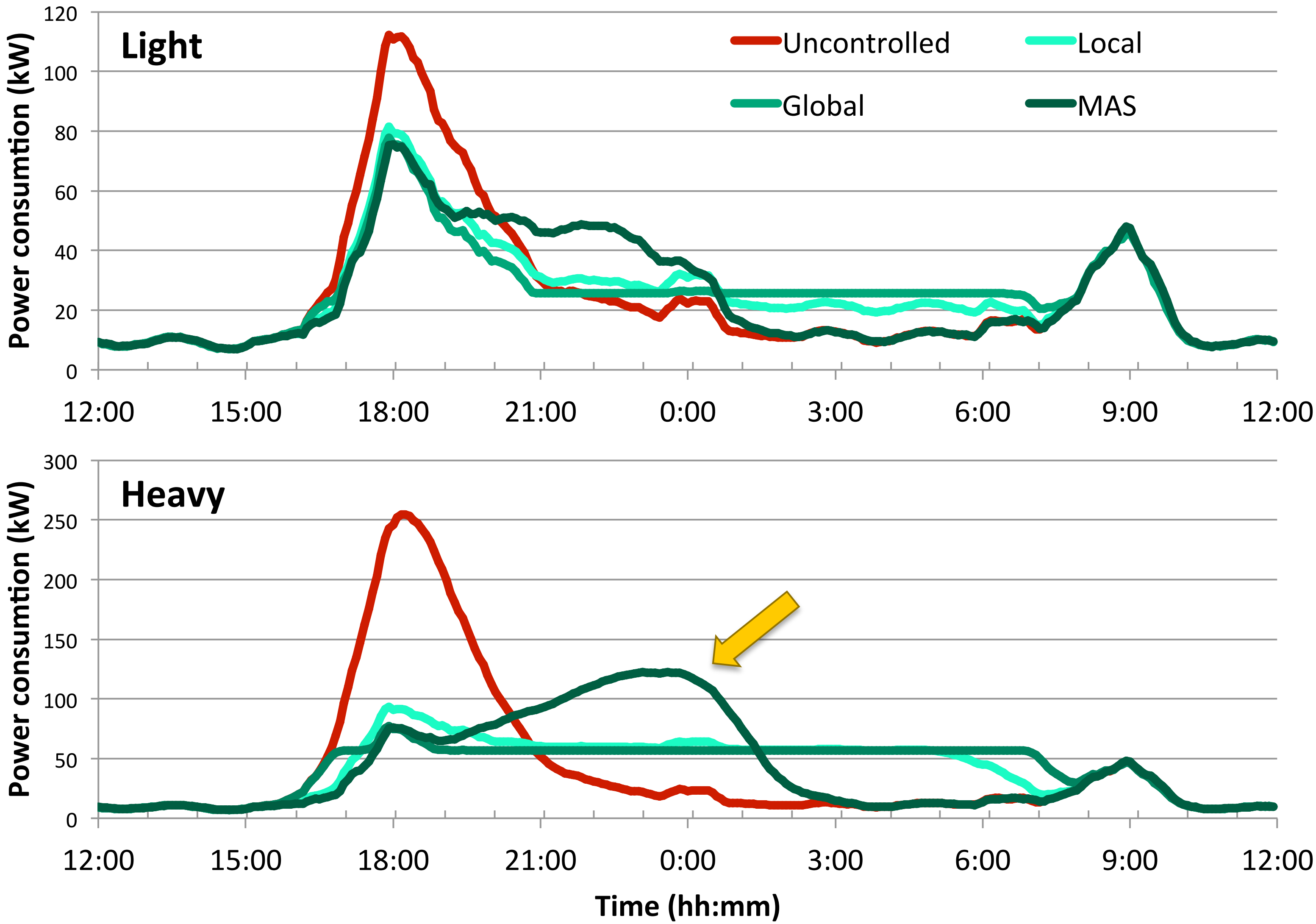
- 63 Households
  - Randomly distributed over 3 phases
  - Spread over 3 feeders



- 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



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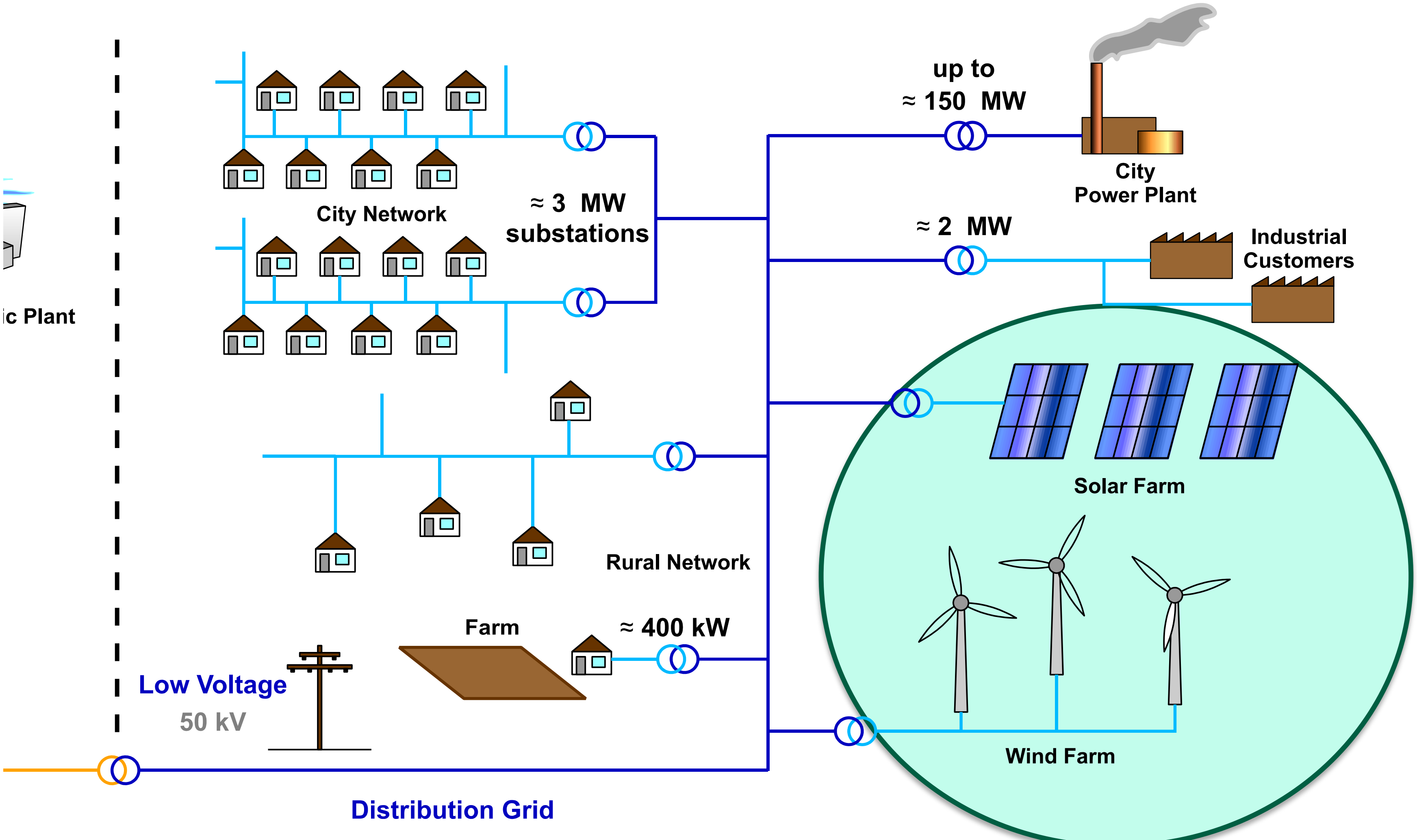
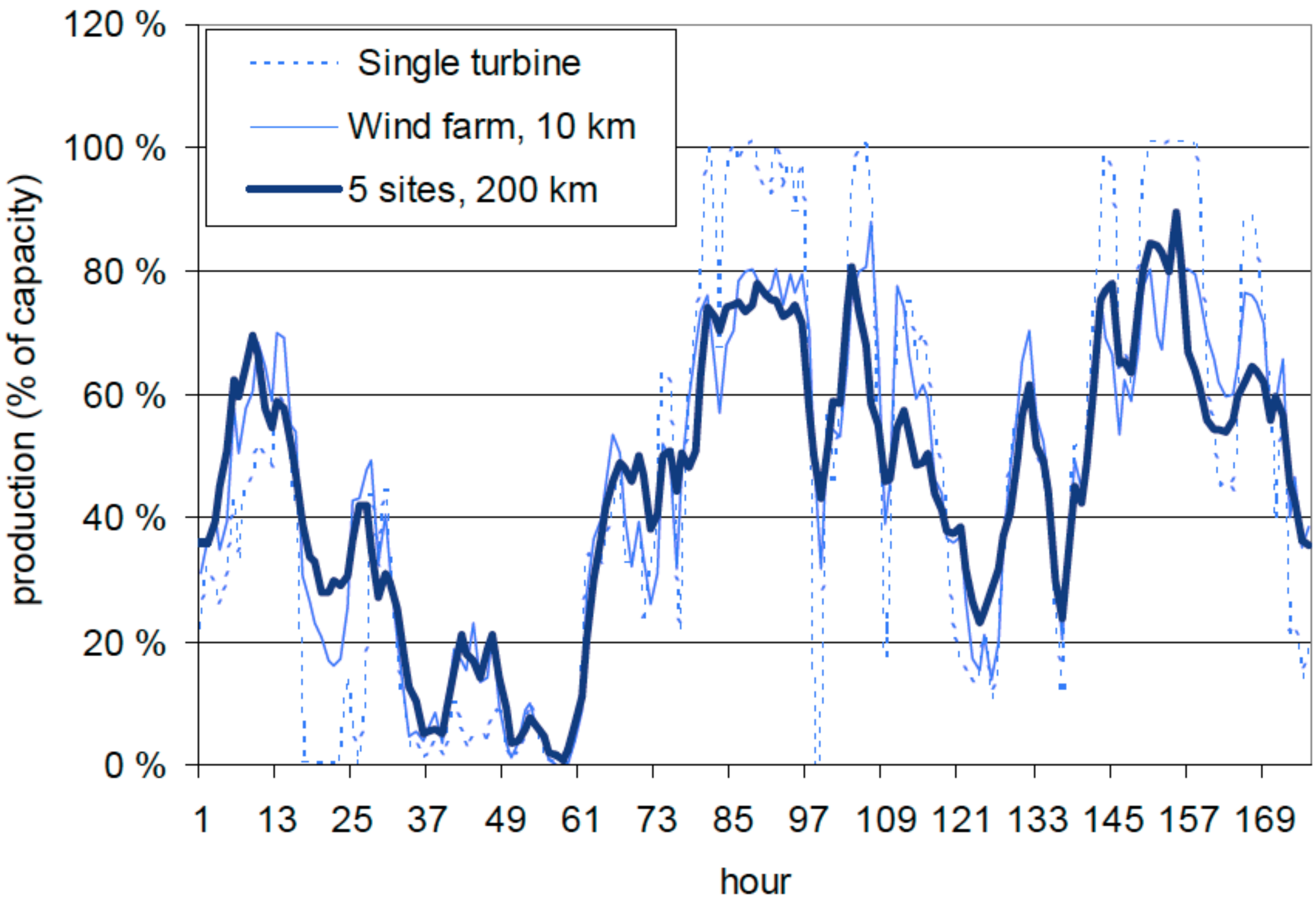
K. Mets, F. De Turck and C. Develder, ***"Distributed smart charging of electric vehicles for balancing wind energy"****, in Proc. 3rd IEEE Int. Conf. Smart Grid Communications (SmartGridComm 2012), Tainan City, Taiwan, 5-8 Nov. 2012, pp. 133-138. doi:10.1109/SmartGridComm.2012.6485972*

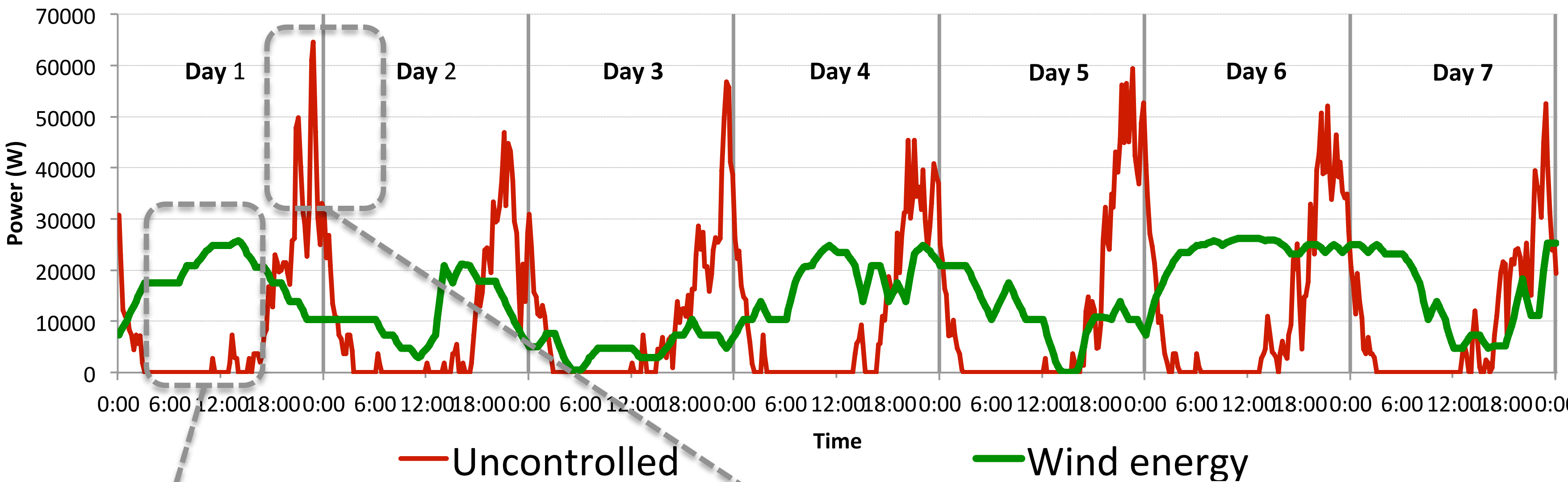
Distributed generation (DG)



A typical wind profile



Wind balancing with EV charging

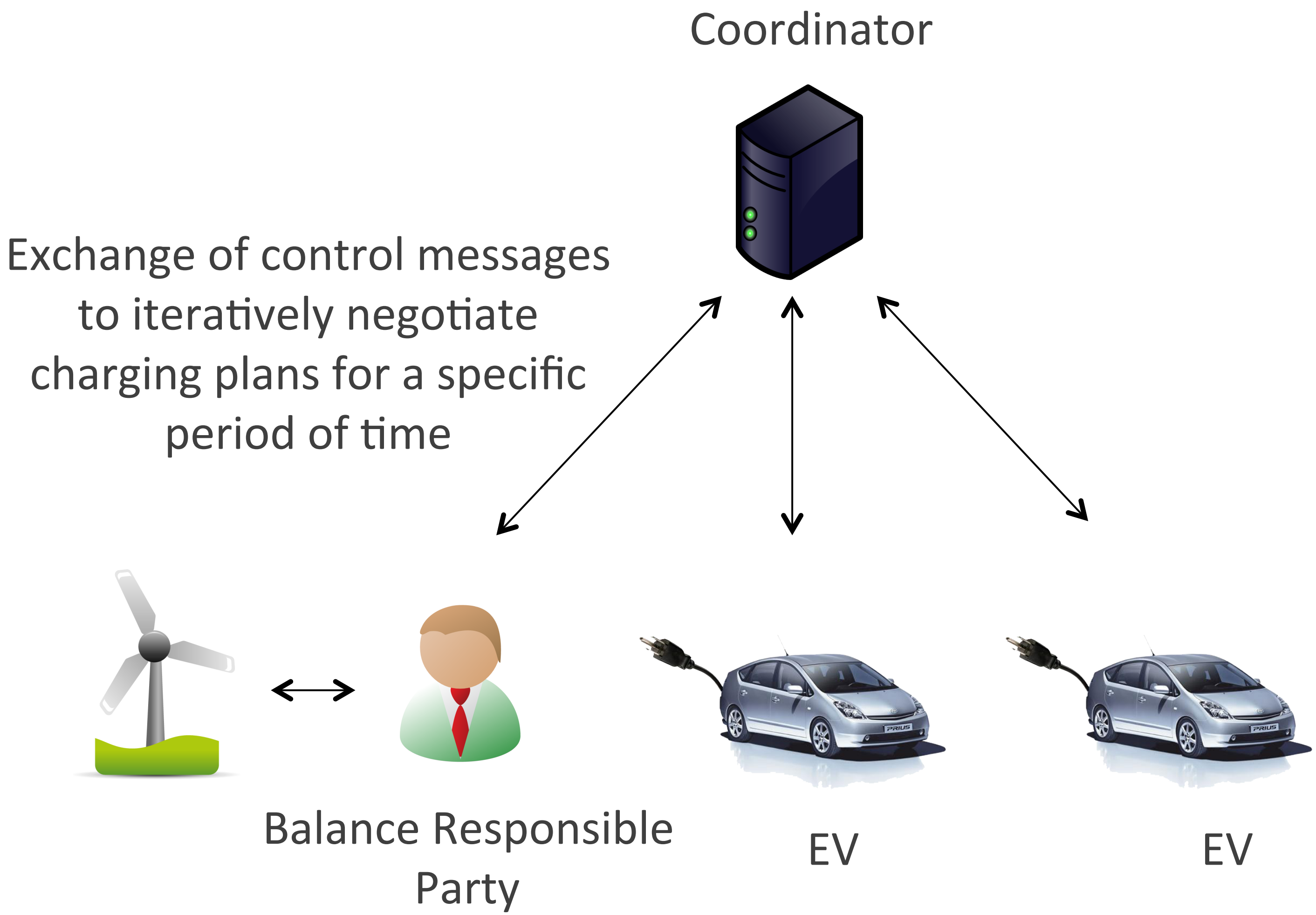


Supply/demand imbalance **High peak loads**

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

Undesirable!

Distributed control



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

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

- 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 λ_t …

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:

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

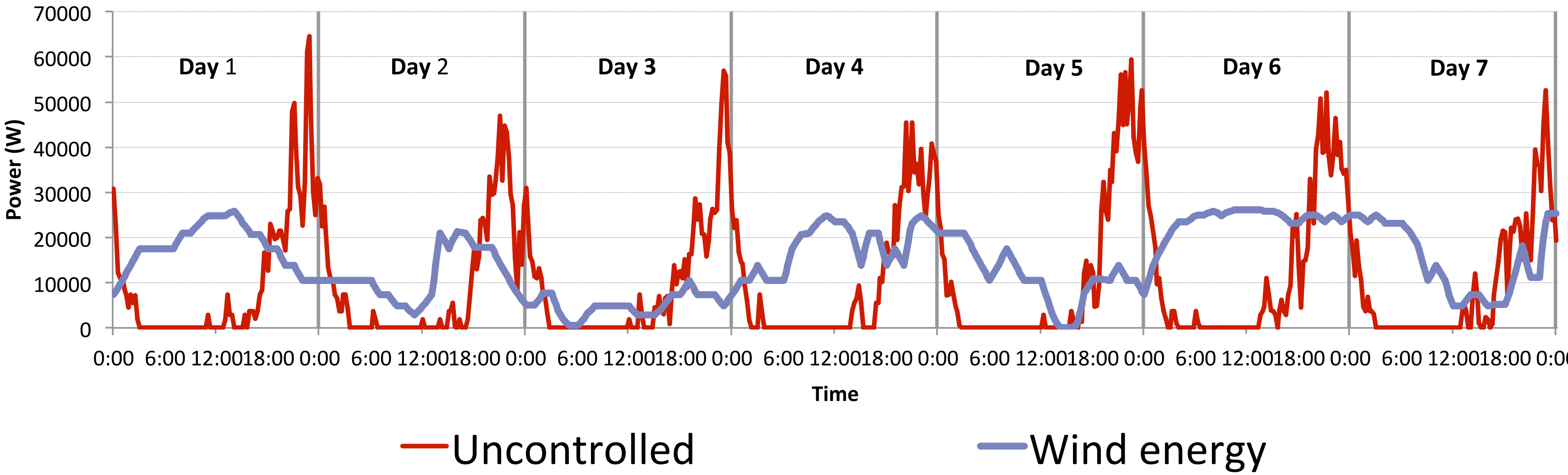
6. Repeat until demand = supply

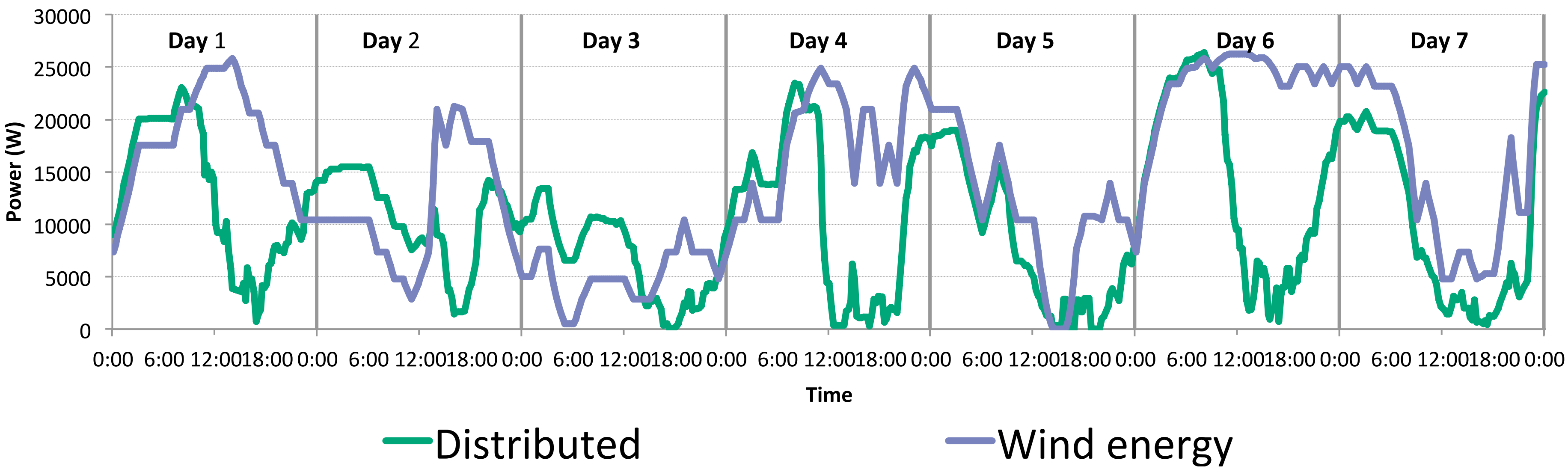
Case study: Algorithms

- **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:

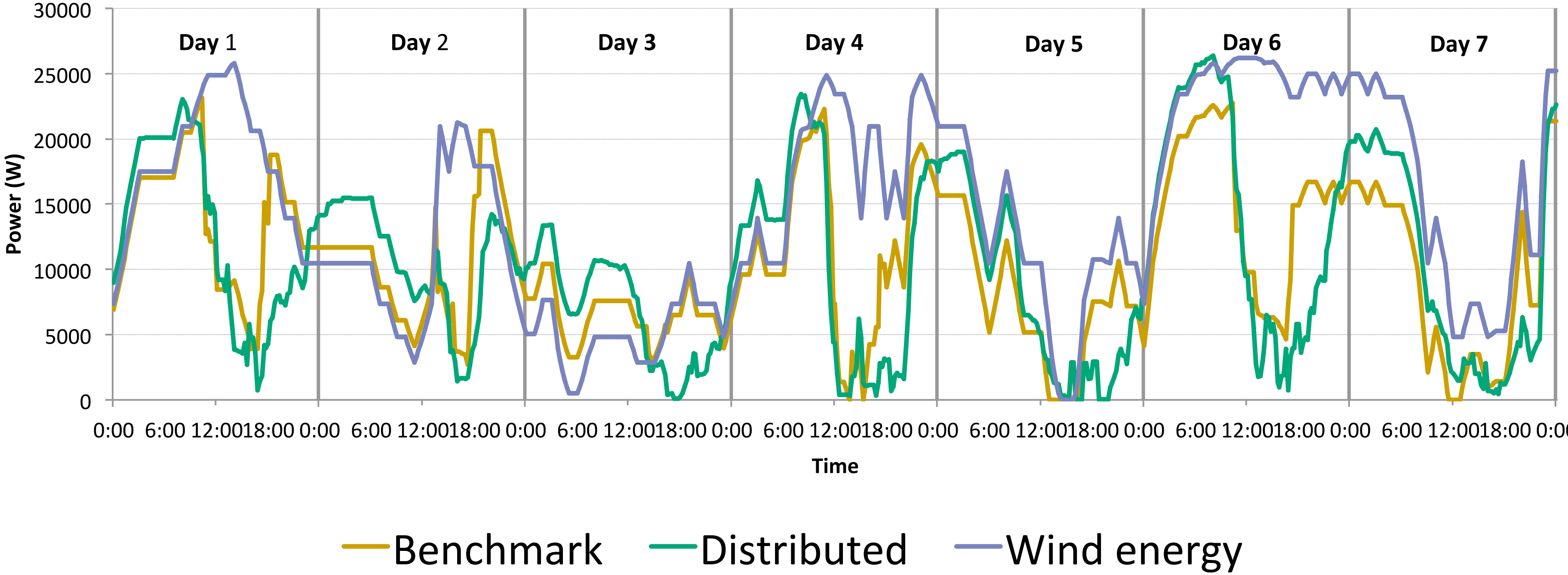
$$\min \sum_{t=1}^{S} \left(w_t - \sum_{k=1}^{K} x_t^k \right)^2$$

Results: Uncontrolled BAU vs. Distributed

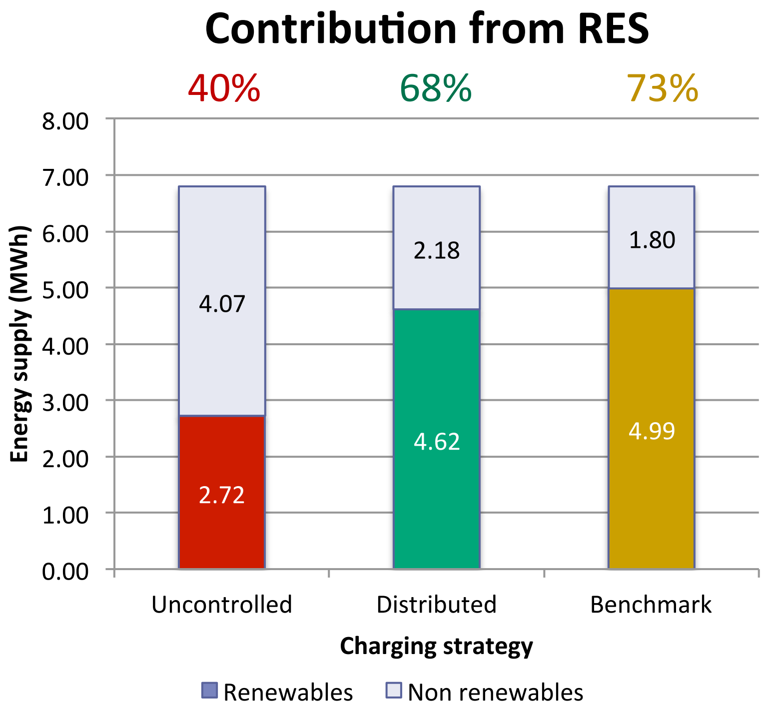


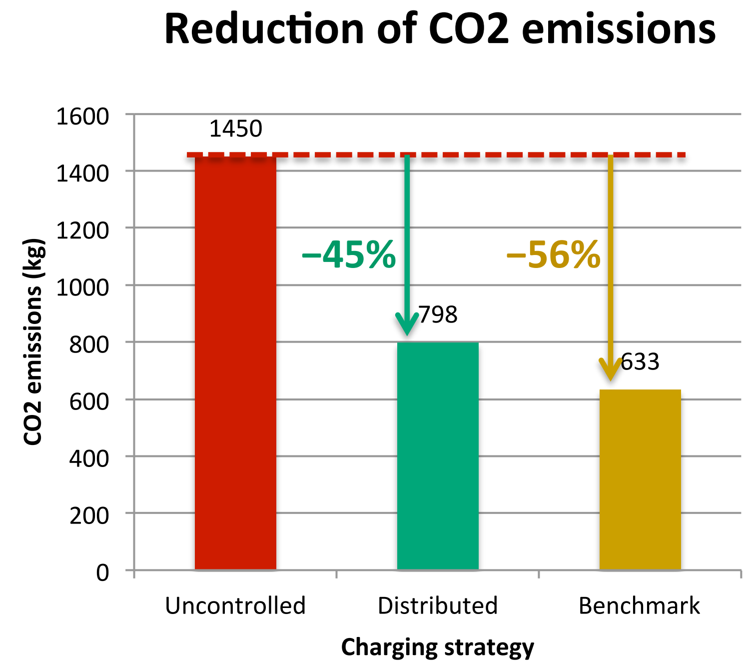


Results: Distributed vs. Benchmark



Results: Energy Mix





Renewables: 7.4 CO2 g/kWh
Non Renewables: 351.0 CO2 g/kWh

- 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

Outline

*K. Mets, F. Depuydt. and C. Develder, **"Two-stage load pattern clustering using fast wavelet transformation"**, IEEE Trans. Smart Grid, 2015. doi:10.1109/TSG.2015.2446935*

Clustering smart metering data

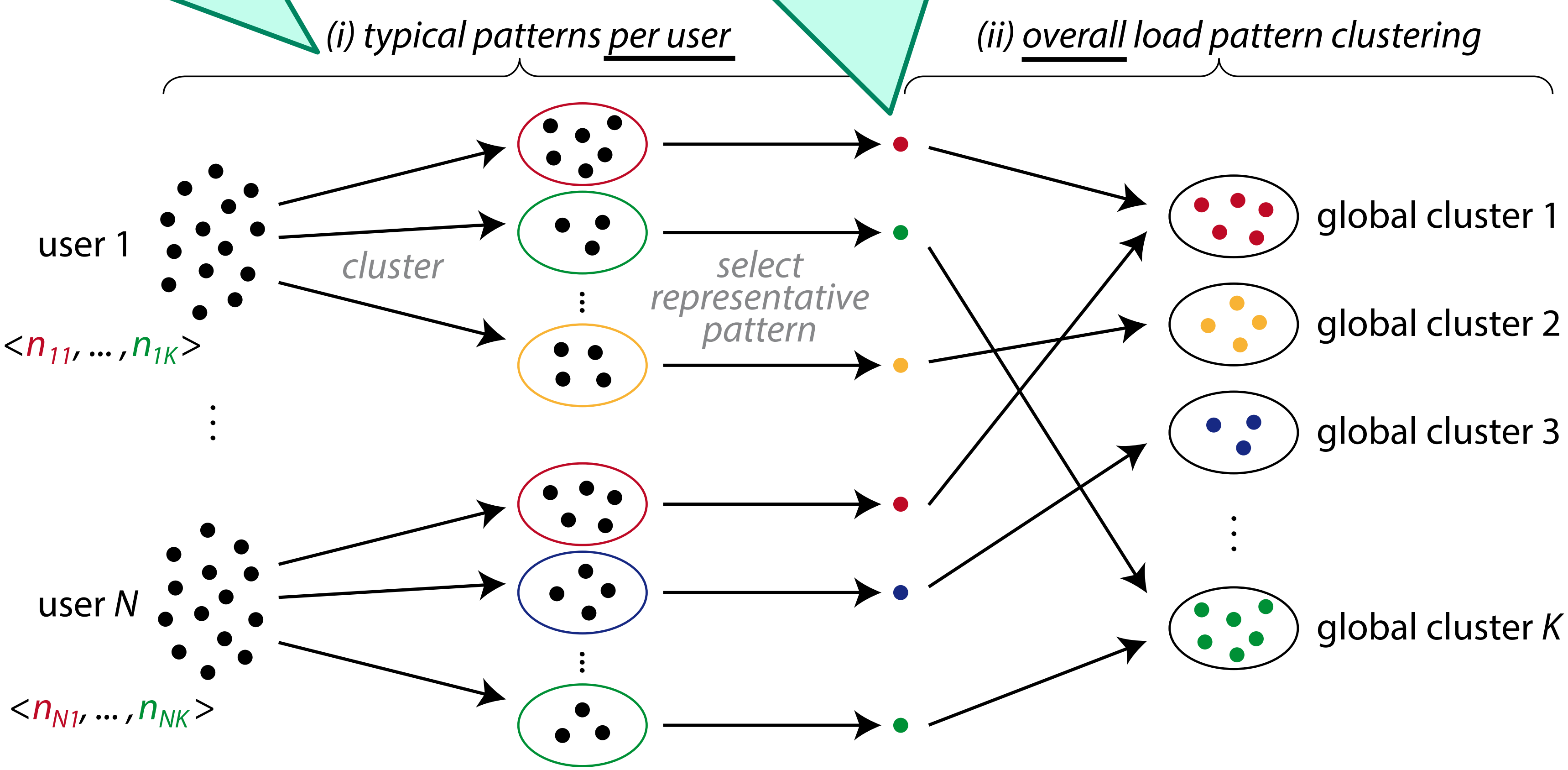
- **Goal:** Identify different types of daily power consumption time series
    1. Single household: distinct types of daily load patterns?
    2. Over whole population: distinct groups of users?

- **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

Can run in parallel,
simultaneously for all users

Representative pattern
= real pattern closest to center



Core ideas

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

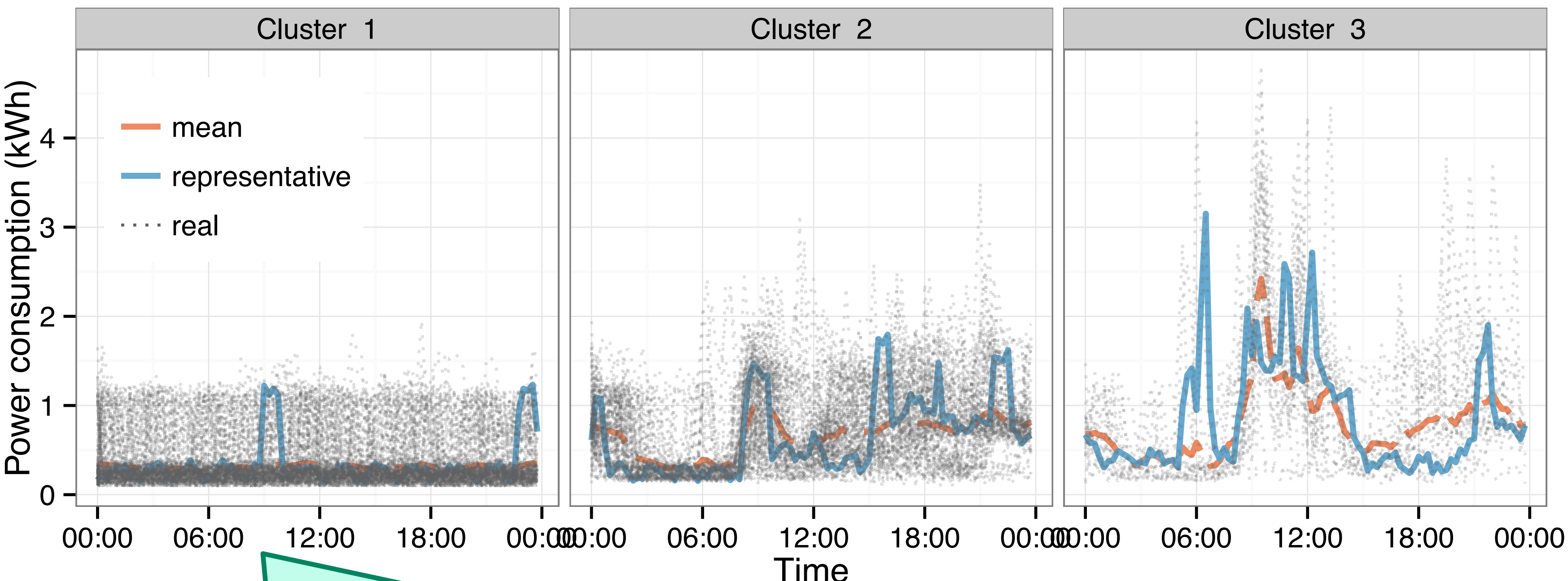
- G-means (instead of k-means) [Hamerly2003]

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

Sample result: Single user

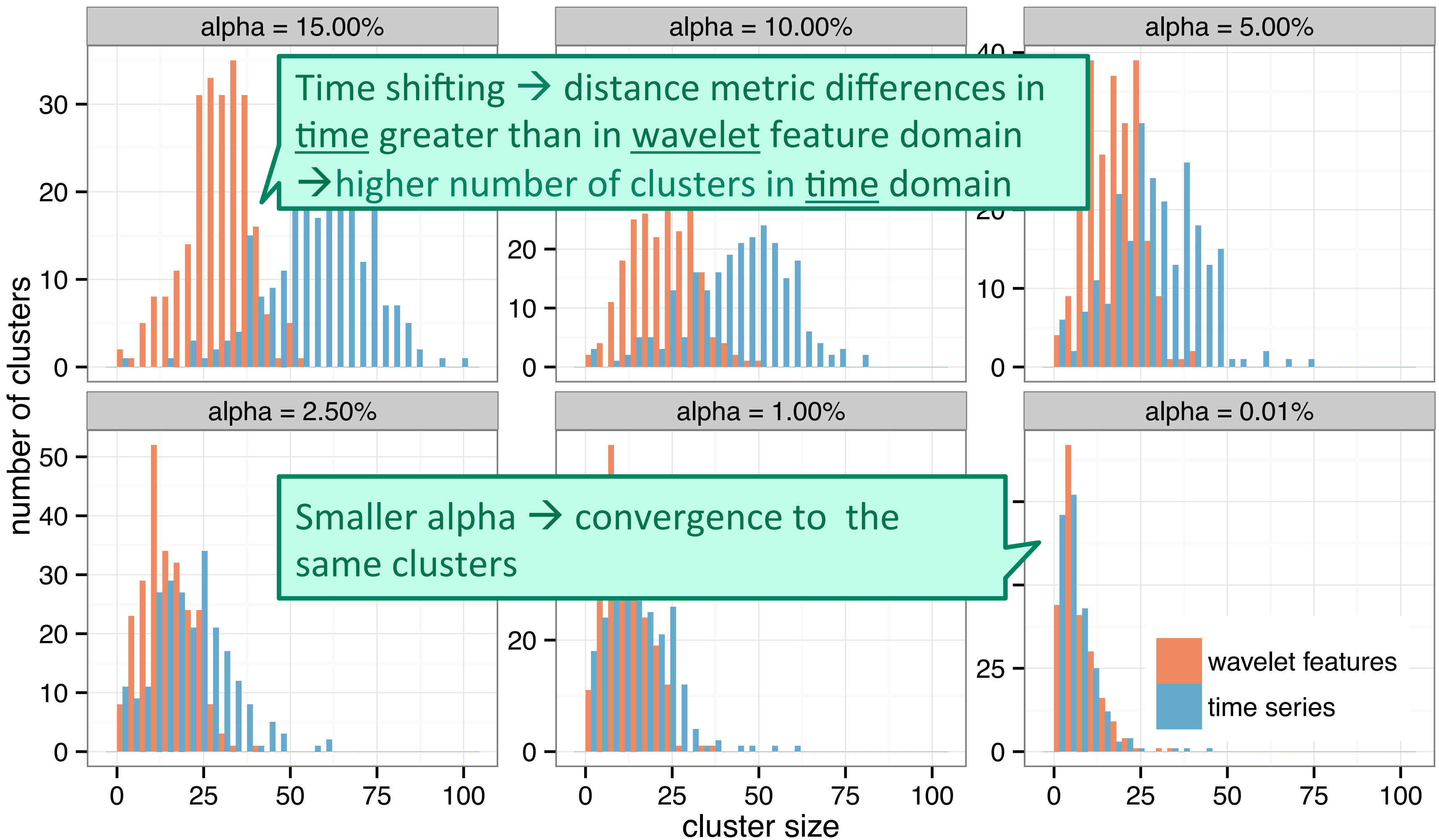
For alpha = 0.01% → low number of clusters

Note: representative ≠ arithmetic mean



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

Time vs wavelet domain: Number of clusters



Conclusions

- Totally unsupervised clustering process
  - No a priori definition of 'typical day', groupings into weekday/weekend …
  - Cluster size/quality controllable via parameter α
- 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)

Outline

C. Develder, N. Sadeghianpourhamami, M. Strobbe, N. Refa, ***"Quantifying flexibility in EV charging as DR potential: Analysis of two real-world data sets"****, submitted 2016*

EV charging analysis: Research questions

1. Types of user behavior?
   - Clustering
   - Generative models

2. Quantification of flexibility?
   - Sojourn vs idle time
   - Demand response potential

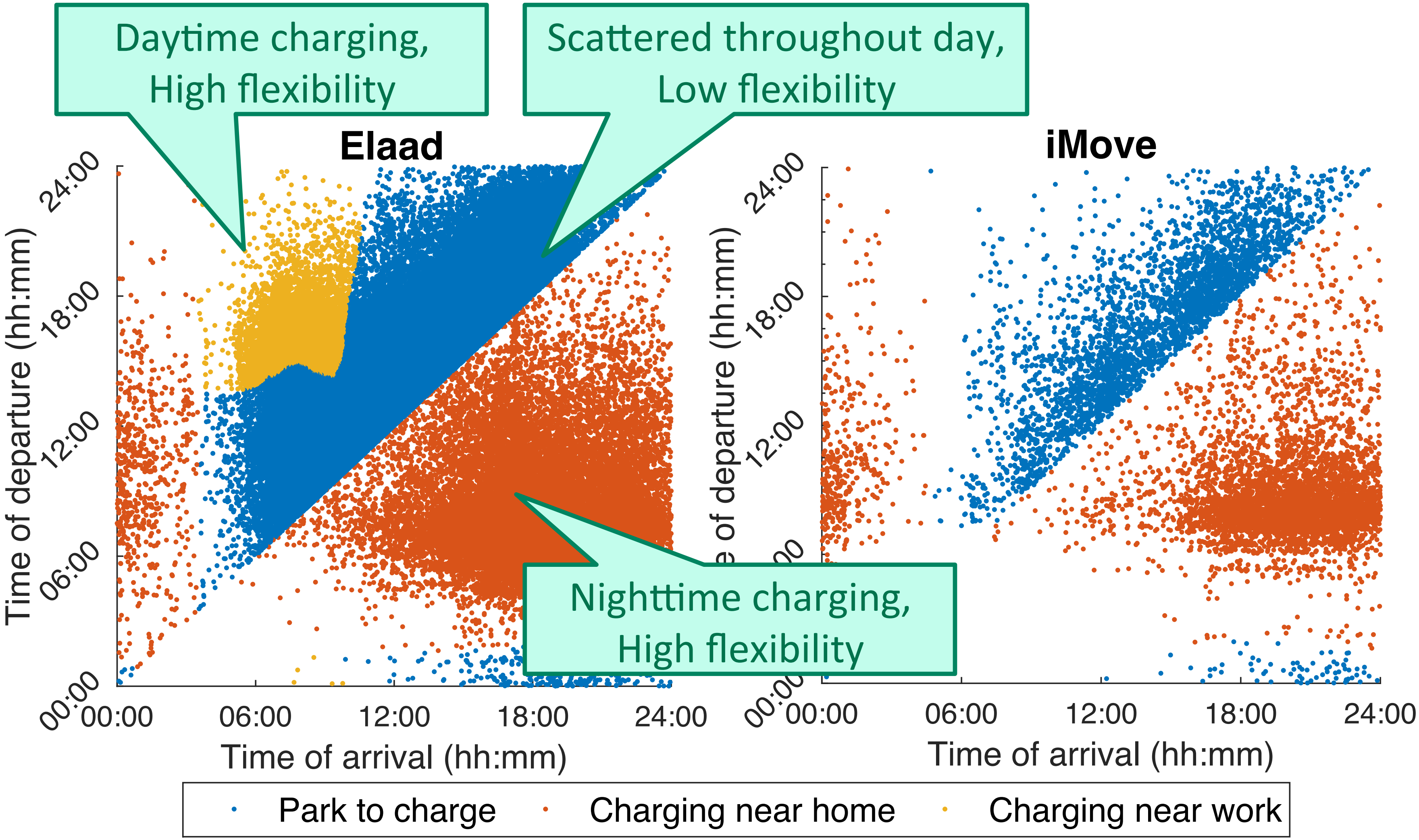
Input: Two real-world data sets

	iMove	ElaadNL*
Period	Mar 2012 – Mar 2013	Jan 2011 – Dec 2015
# Sessions	8,520	1,141,849
# Users†	134	53k
Car type	Full EV	Unknown mix
Charge point	At home	Public
Trip details	Yes	No

*: Results are based on sessions from 1 Jan 2015 – 31 Mar 2015 (N = 90,562)

†: In iMove, at any point in time, up to 50 users were active. For ElaadNL, sessions are tied to a particular charging car**d**.

User behavior: 3 Types of behavior

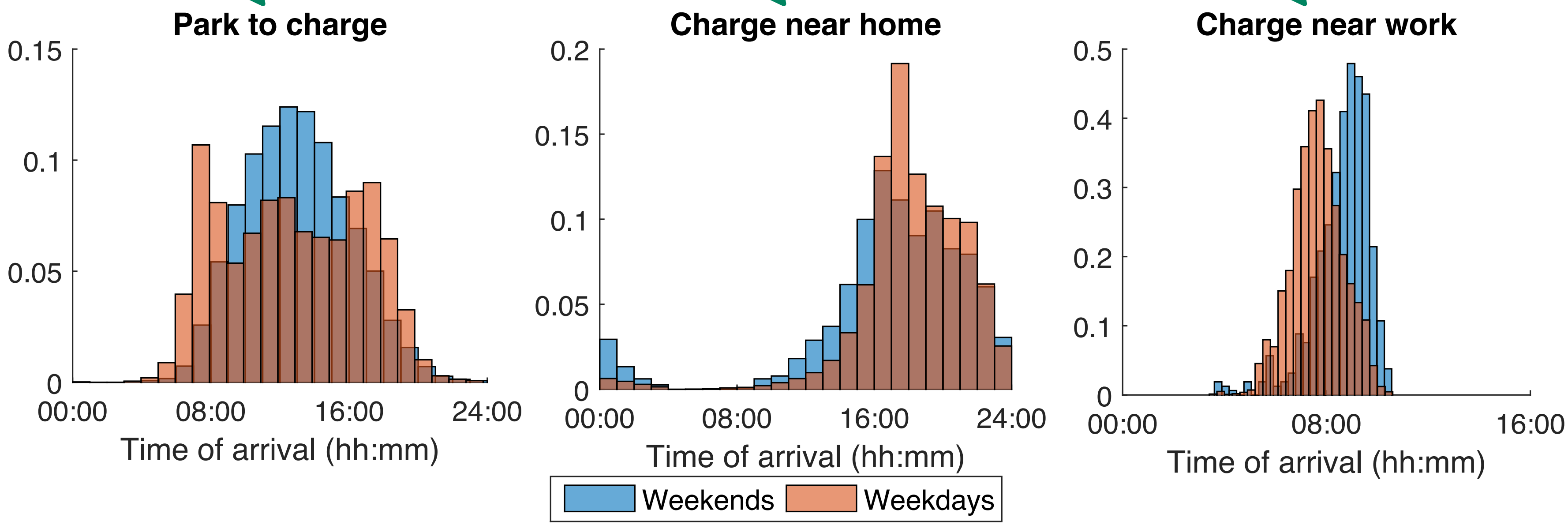


User behavior: Distributions of *arrival times*

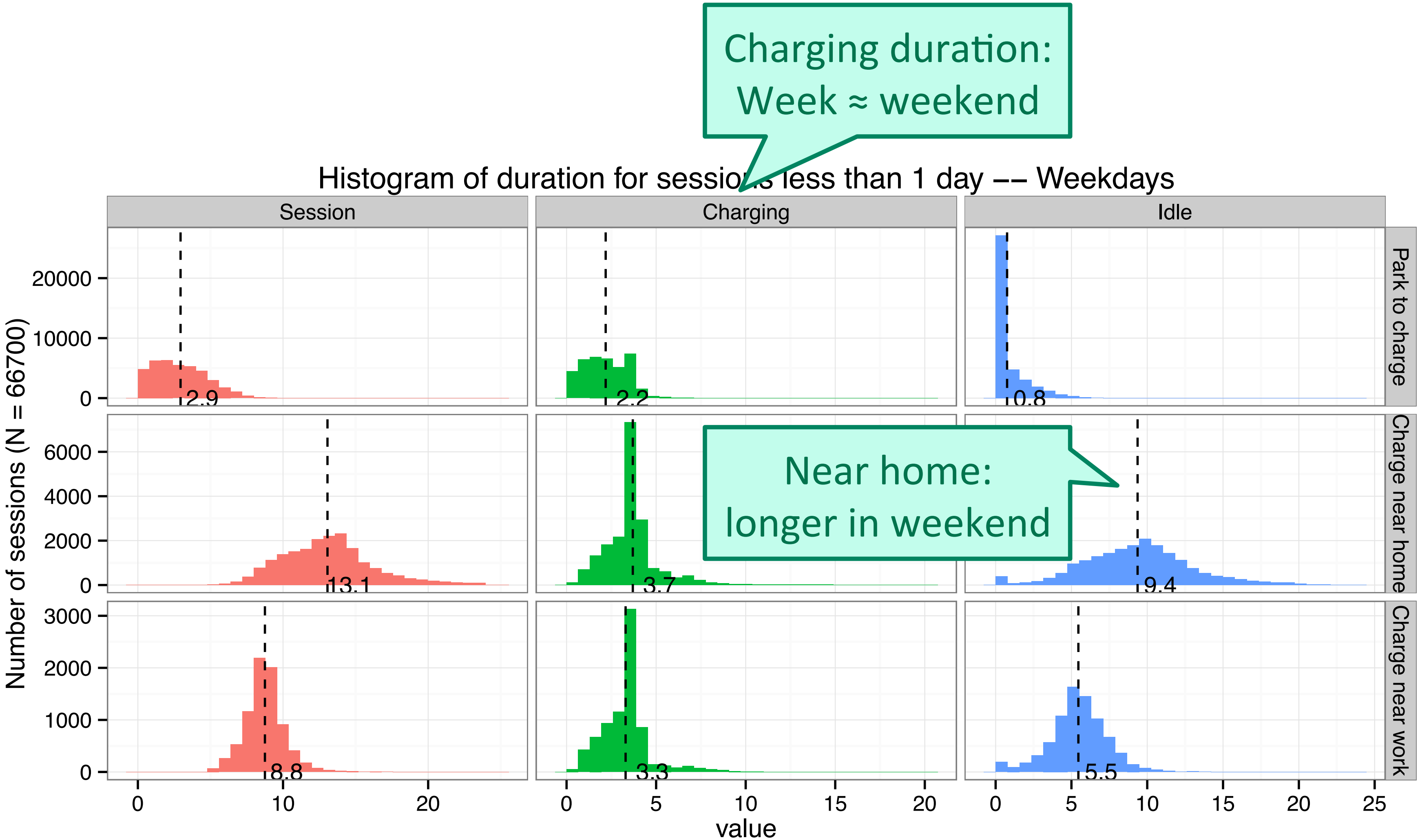
Different week vs weekend pattern

Slightly more spread in weekend

Shift to later times in weekend



User behavior: *Session* duration – Weekdays



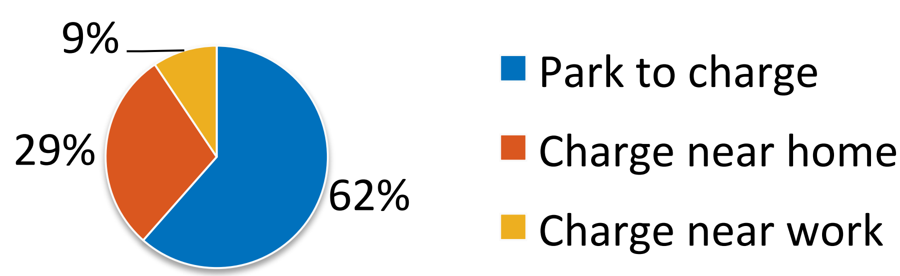
User behavior: *Session* duration – Weekends

User behavior: Statistical models

Table II: Fitted distributions for total sojourn and idle times

			Sojourn time (δ^{sojourn})			Idle time (δ^{idle})		
Cluster	Sub-cluster departures	Fraction	Distr.	Normalized distr. parameters*	[min, max] (hours)	Distr.	Normalized distr. parameters*	[min, max] (hours)
Park to charge (61.5%)	in 1^{st} 24 h	98.9%	Beta	$\alpha = 1.91,\ \beta = 14.22$	$[0.02, 23.91]$	Beta	$\alpha = 0.31,\ \beta = 10.04$	$[0, 23.66]$
	in 2^{nd} 24 h	0.9%	Gamma	$\alpha = 1.24,\ \beta = 6.40$	$[24.00, 36.11]$	Logistic	$\mu = 0.64,\ s = 0.06$	$[5.05, 32.35]$
	in 3^{rd} 24 h	0.1%	Gamma	$\alpha = 1.40,\ \beta = 5.01$	$[48.01, 59.93]$	Logistic	$\mu = 0.62,\ s = 0.08$	$[34.21, 55.11]$
Charge near home (29.1%)	in 1^{st} 24 h	95.4%	Logistic	$\mu = 0.56,\ s = 0.08$	$[0.02, 23.99]$	Normal	$\mu = 0.42,\ \sigma^2 = 0.17$	$[0, 23.53]$
	in 2^{nd} 24 h	3.3%	Beta	$\alpha = 2.59,\ \beta = 1.95$	$[28.13, 47.95]$	Normal	$\mu = 0.57,\ \sigma^2 = 0.16$	$[19.37, 47.86]$
	in 3^{rd} 24 h	0.8%	Beta	$\alpha = 2.44,\ \beta = 1.61$	$[52.84, 72.00]$	Normal	$\mu = 0.57,\ \sigma = 0.21$	$[47.25, 70.00]$
	in 4^{th} 24 h	0.3%	Beta	$\alpha = 2.91,\ \beta = 1.39$	$[74.75, 95.86]$	Normal	$\mu = 0.64,\ \sigma^2 = 0.20$	$[69.05, 93.73]$
Charge near work (9.4%)	in 1^{st} 24 h	99.6%	Logistic	$\mu = 0.27,\ s = 0.06$	$[5.00, 18.52]$	Logistic	$\mu = 0.35,\ s = 0.07$	$[0, 15.54]$

* The parameters of distributions are the following: (i) *Normal*: mean μ and variance σ^2, (ii) *Beta*: shape parameters α and β, (iii) *Gamma*: shape α and rate β, (iv) *Logistic*: location parameter μ and scale parameter s. Note that the parameter values are reported for fits of normalized data, i.e., durations are rescaled per sub-cluster as $\delta_{\text{normalized}} = \frac{\delta - \min}{\max - \min}$.



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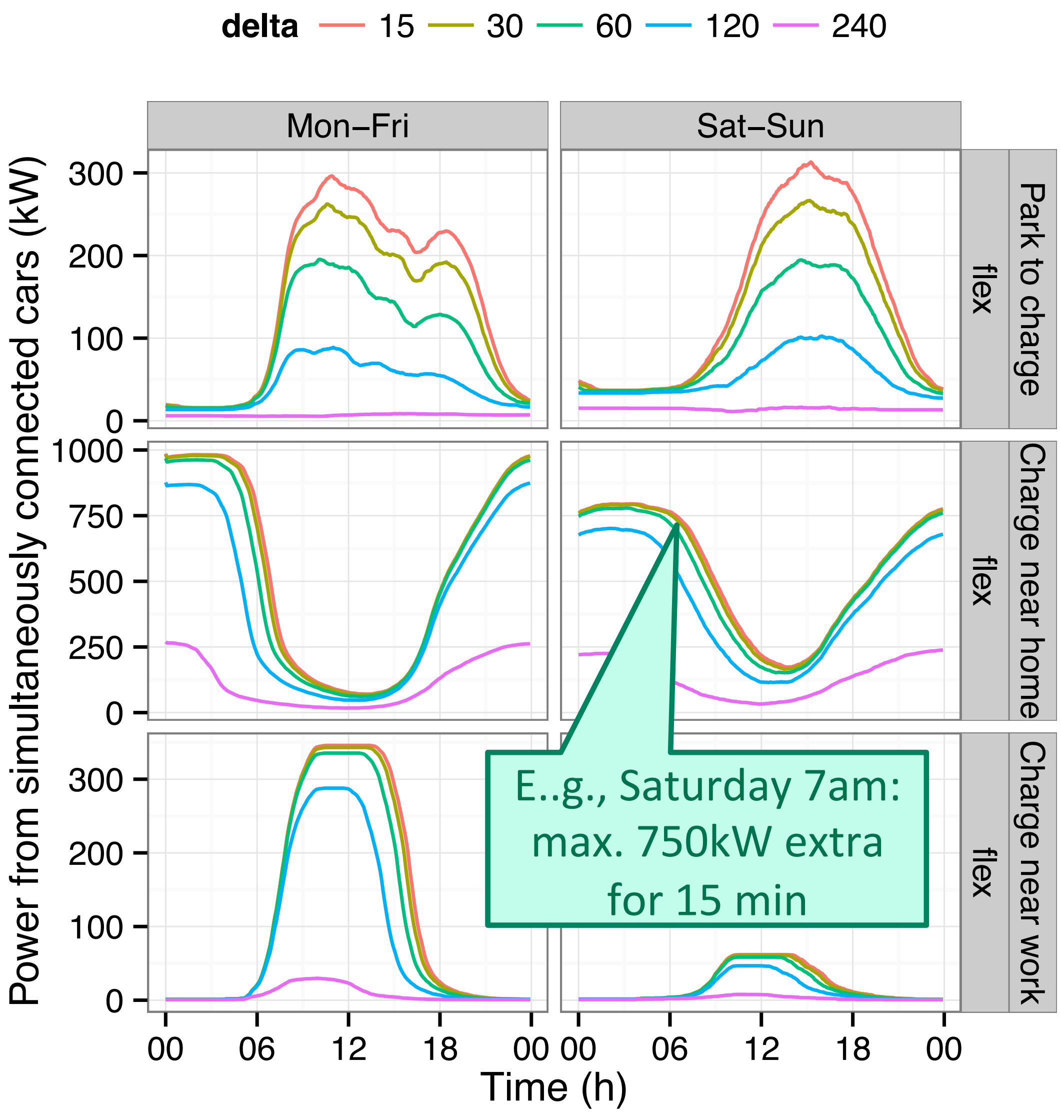
Quantification of flexibility: Calculation

Upper bound: we disregard impact of using/ suppressing power in [*t*,*t*+Δ] on flexibility at other times *t'*

$P_{FLEX}(t, \Delta)$ = Maximal power that DR could either consume constantly, or not at all, in interval [t, t+Δ]

- Charging session has to include [t, t+Δ]
- Charging duration ≥ Δ [else we could not consume in full interval]
- Flexibility = session duration − Δ ≥ charging duration [we can move it away]

Quantification of flexibility: Result



- Park to charge:
  - Daytime flexibility
  - Weekend: ≈ volume, but ≠ timing
- Near home:
  - Nighttime flex
  - Weekend: lower & more spread
- Near work:
  - Daytime flex
  - Low in weekend

Conclusion on flexibility analysis EVs

- Real world data set
- Three major types of charging sessions
- Statistical models of user behavior
- Methodology to quantify flexibility

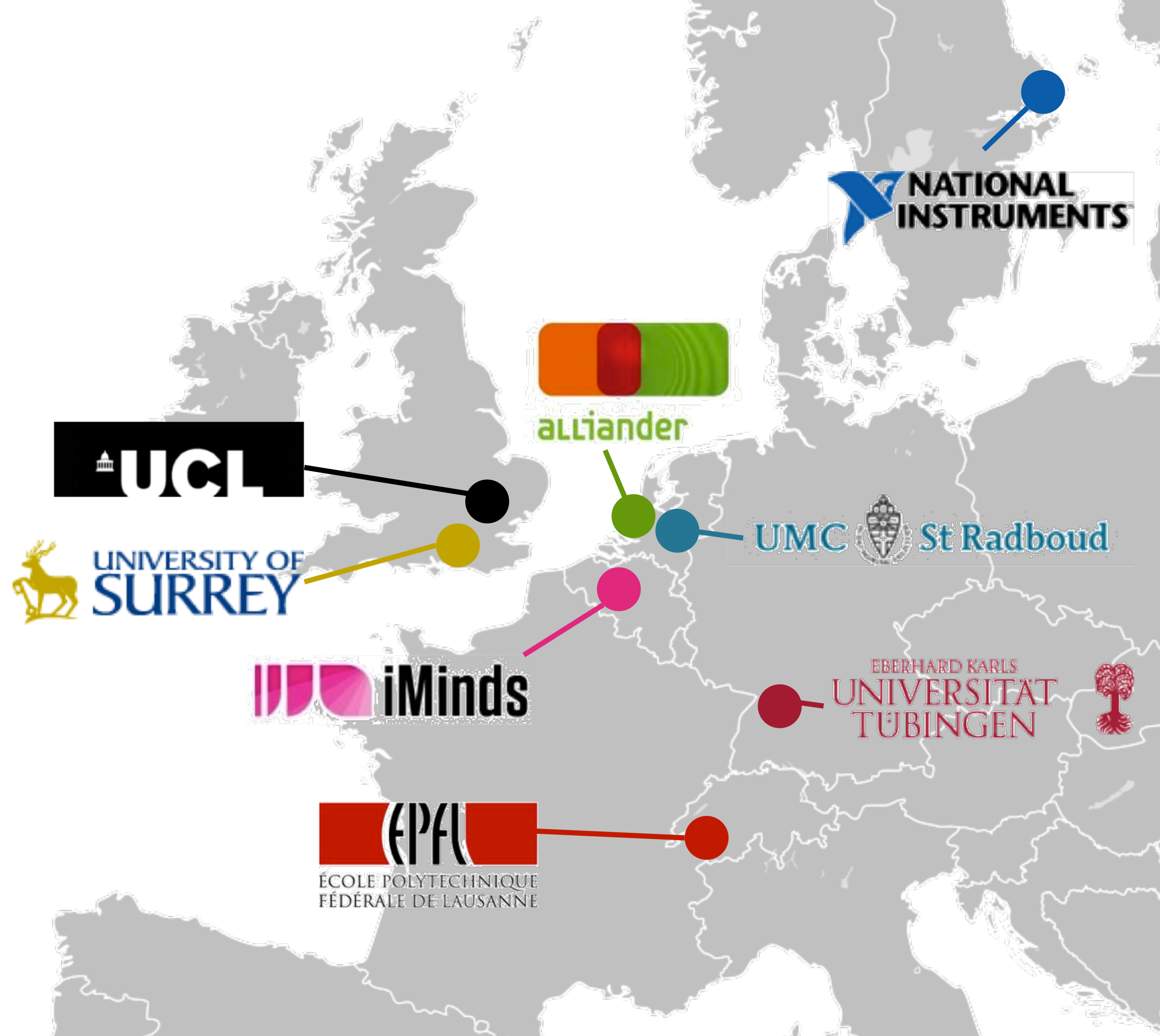
- Application?
  E.g., extrapolation of iMove data to 3% of Flemish fleet by 2020:
  - ~100k cars out of ~3.2M
  - E.g., noon in weekend => can have ~7MW extra for 2h

Outline

*W.K. Chai, et al., **"An information-centric communication infrastructure for real-time state estimation of active distribution networks"**, IEEE Trans. Smart Grid, Vol. 6, No. 4, Jul. 2015, pp. 2134-2146. doi:10.1109/TSG.2015.2398840*

C-DAX: Cyber-secure Data and Control Cloud for power grids

- Project FP7-ICT-2011-8
- Oct. 1, 2012 – Feb. 19, 2016
- Budget: 4.3M EUR
  EU-funding: 2.9M EUR
- More info:
  http://www.cdax.eu



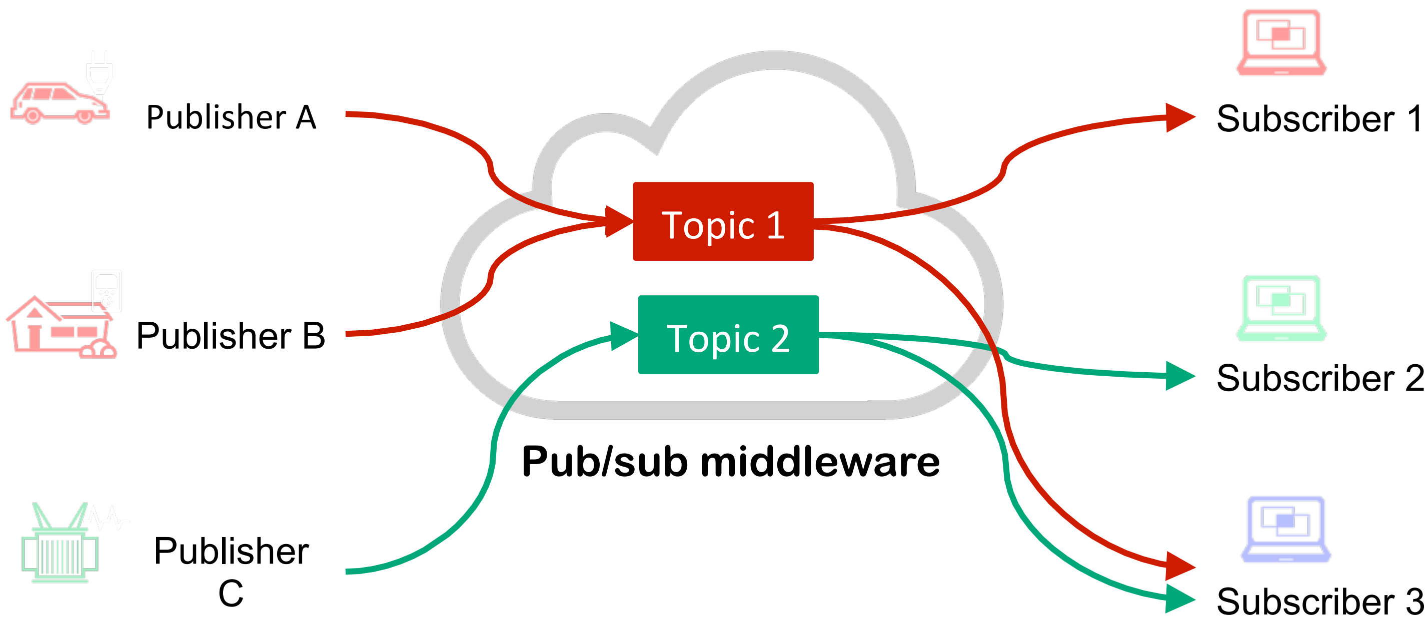
Smart grid communication pattern variation

- **1-to-1**: e.g., control messages for specific assets
- **1-to-M**:
  - *Broadcast*: e.g., energy offers in demand response schemes
  - *Anycast*: e.g., offer for voltage regulation by any suitable subset of EVs located in a certain area
- **M-to-1**: e.g., energy consumption reports in demand response or smart metering
- **M-to-N**: e.g., multiple charging offers from different charging stations to multiple EVs
- **Asynchronous** communication in dynamic scenarios:
  e.g., EVs come and go, retrieve/deliver data while connected to the network

ICN = Information Centric Networks

- Alternative for Point-to-point networks
  - Explicit point-to-point connections from producer to predefined consumers → need to know/config all IPs
- ICN paradigm = **based on topic rather than IP address**
  - Consumers “pull” or “subscribe to” the data “topics”
  - Agnostic of who produced and when/where info is stored
  - Decoupling of producers/consumers
- Advantages:
  - Inherent **security**: hosts do not know each other’s locations
  - Overlay network **management**:
    - Management of IP connections, optimal placement of the data within the cloud, resilience…
    - In-network management and processing (e.g., caching, aggregation, filtering, rate adaptation, traffic engineering …)

Topic-based Communication



Benefits of decoupling publishers and subscribers

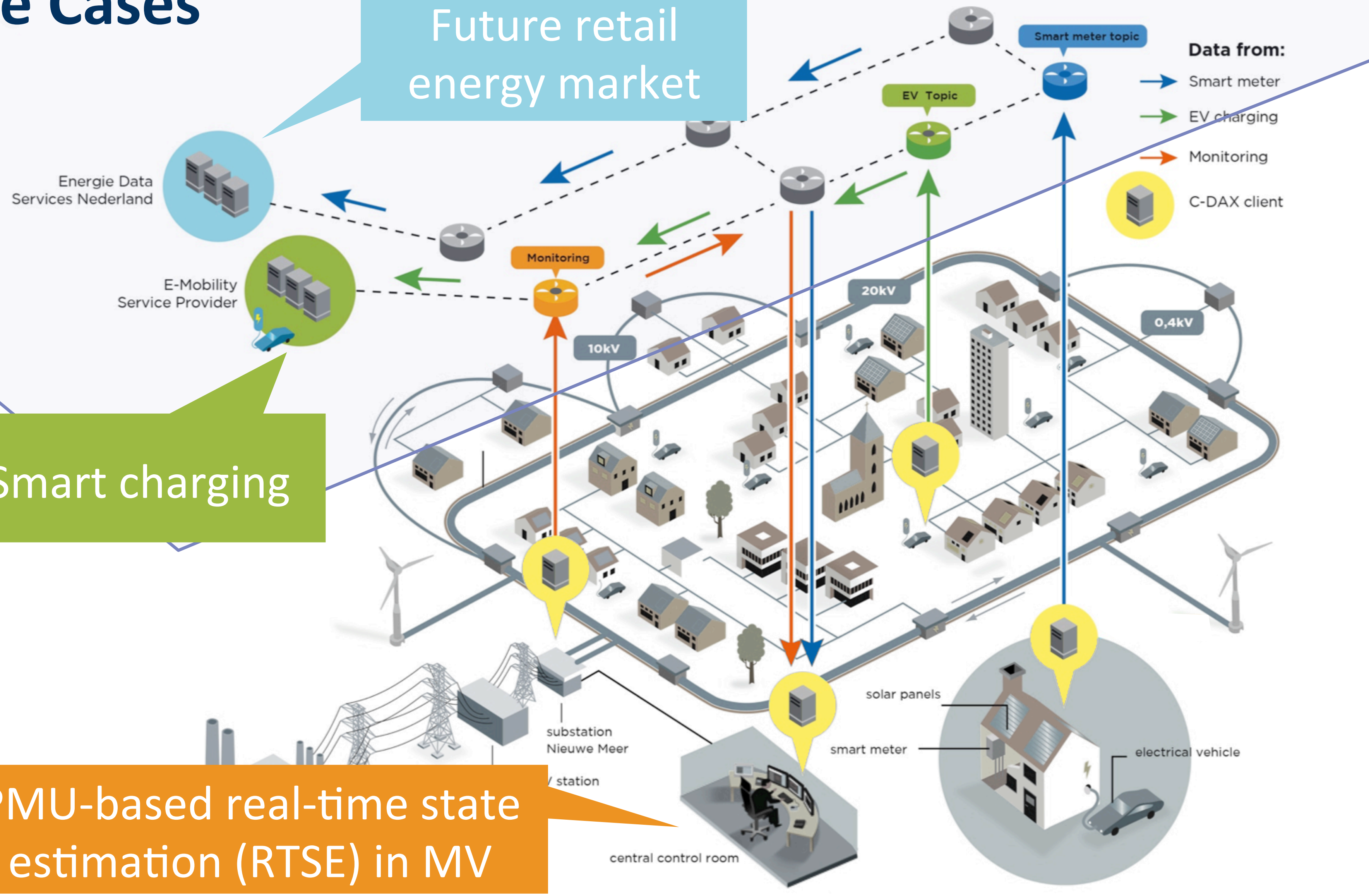
- Communication partners do not need to know each other
- Asynchronous communication possible
- Facilitating extensibility, management and configurability

Use Cases

Future retail energy market

Smart charging

PMU-based real-time state estimation (RTSE) in MV



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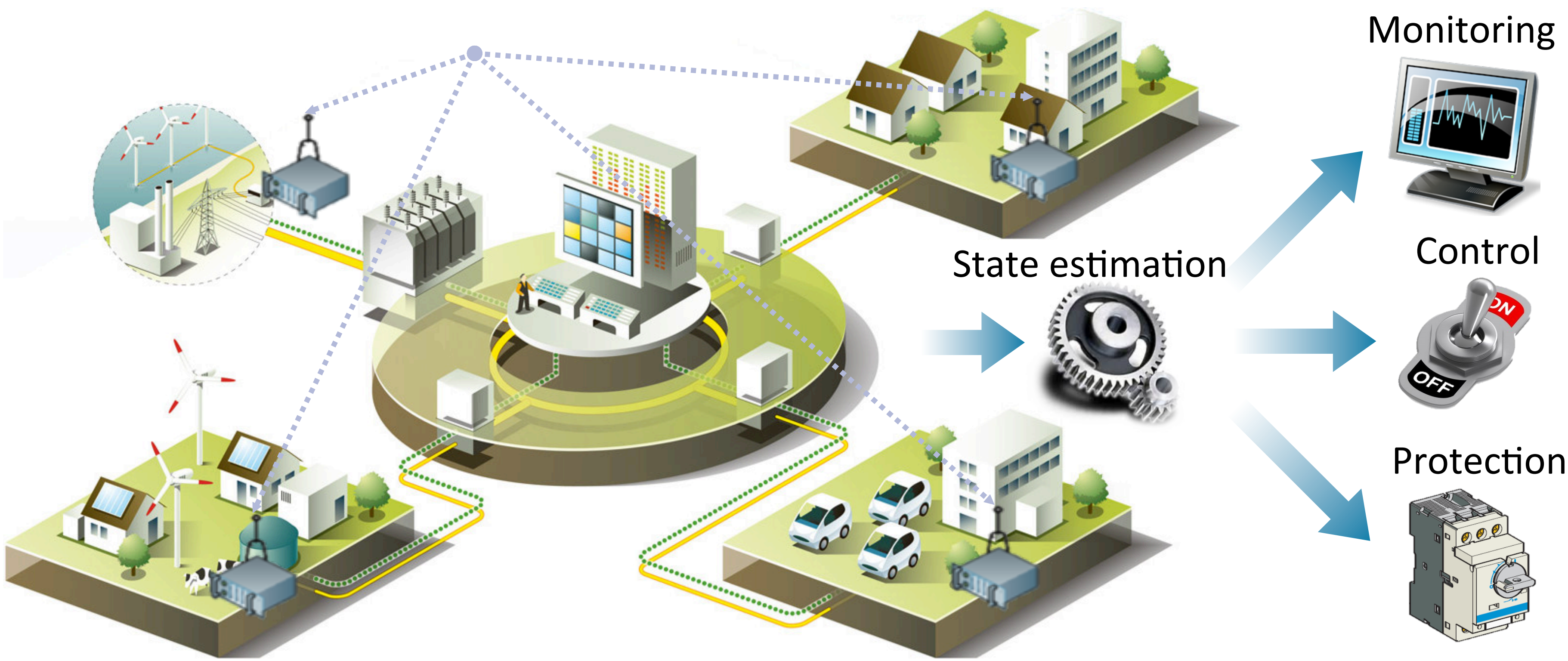
Use Case: Real-time state estimation of ADNs



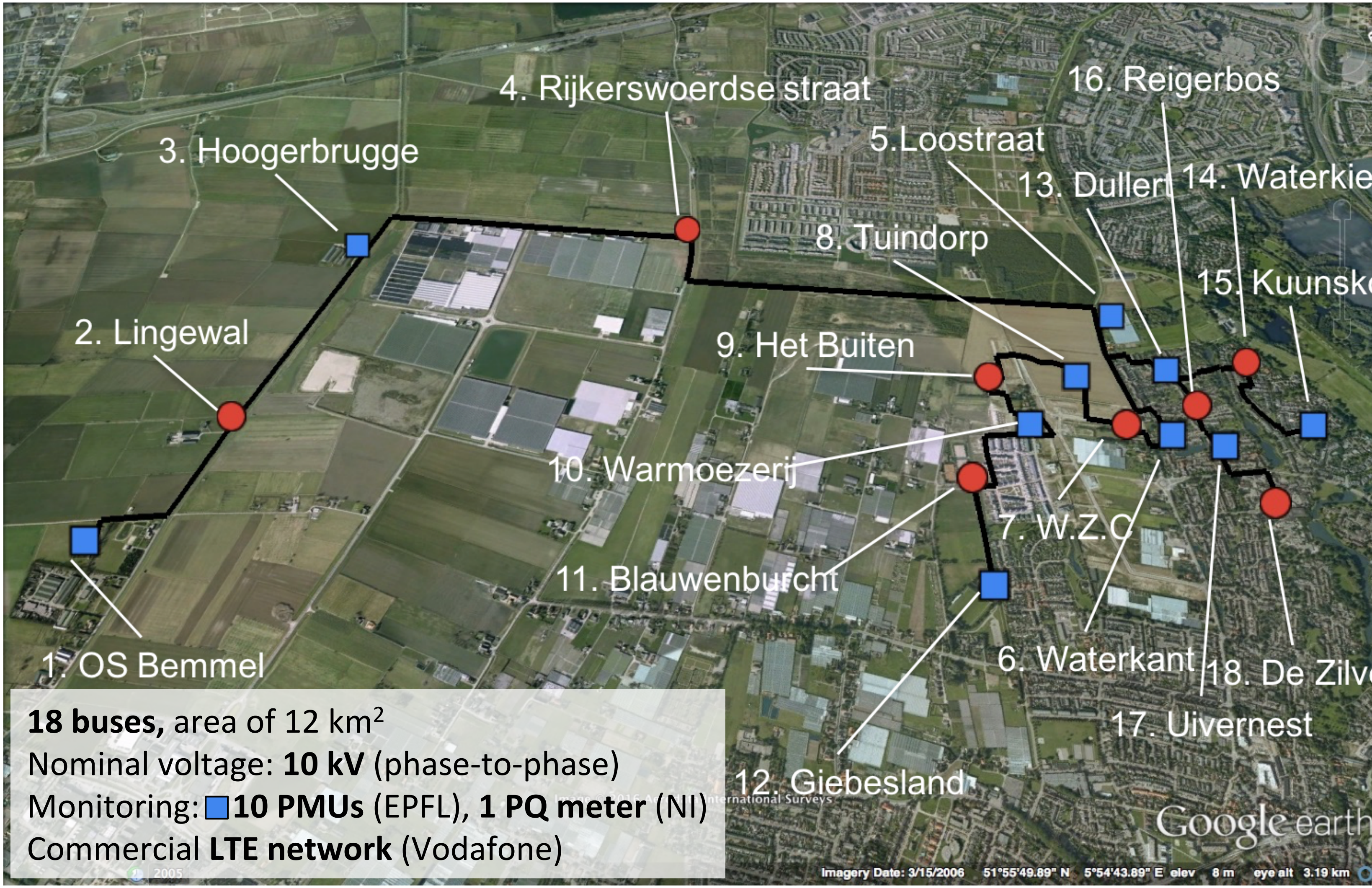
Network in ***normal*** operation:

- Congestion management
- Optimal V/P control
- Optimal dispatch of DER

Network in ***emergency*** conditions:

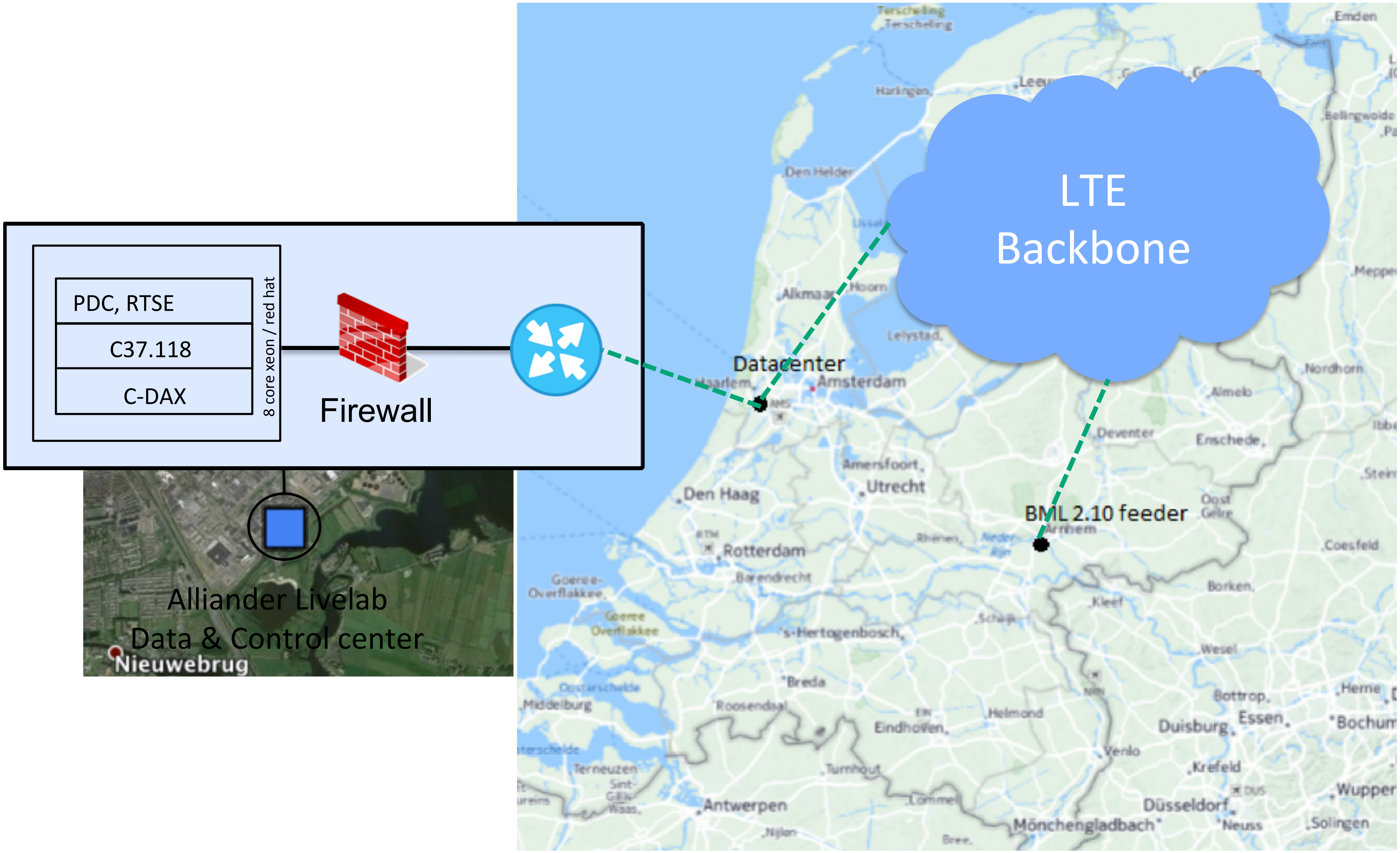
- Islanding detection
- Fault identification
- Fault location

Field trial setup: Feeder of Alliander (Arnhem, NL)



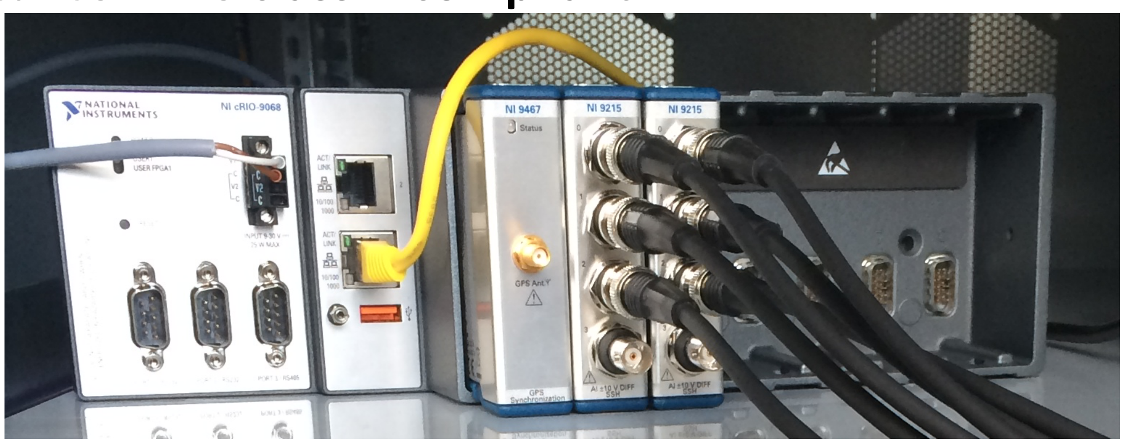
18 buses, area of 12 km^2
Nominal voltage: **10 kV** (phase-to-phase)
Monitoring: **10 PMUs** (EPFL), **1 PQ meter** (NI)
Commercial **LTE network** (Vodafone)

Field trial setup: Alliander data center

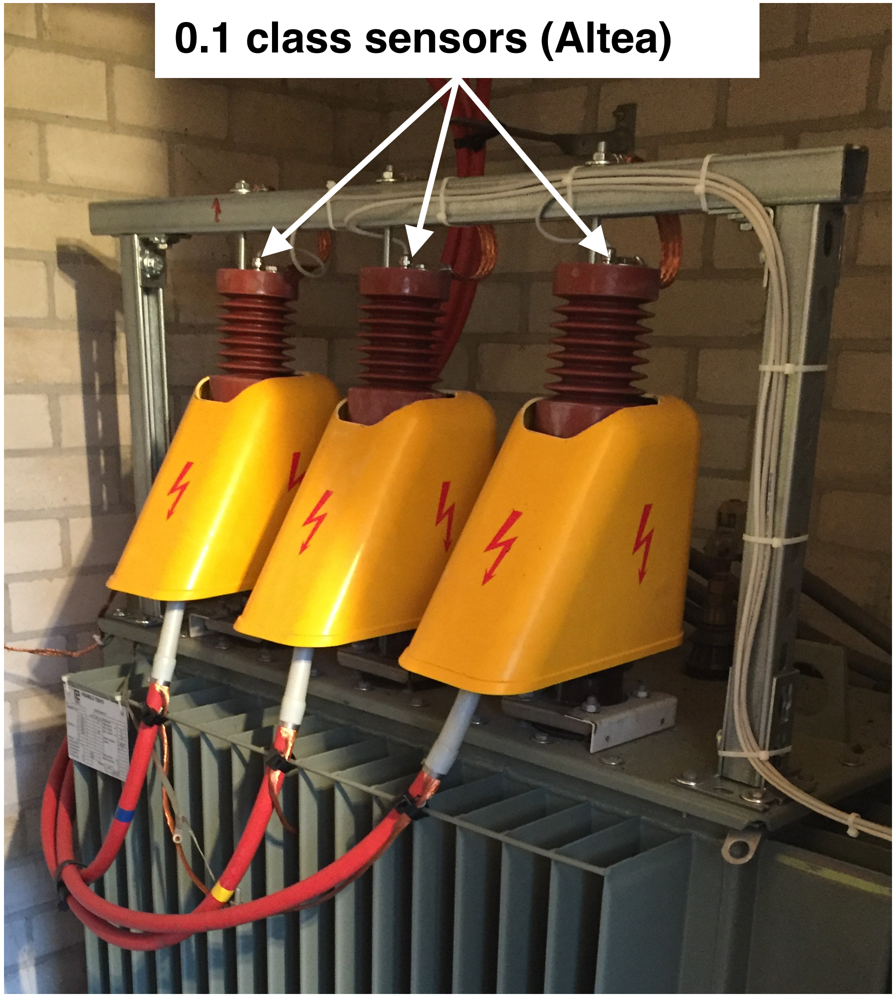


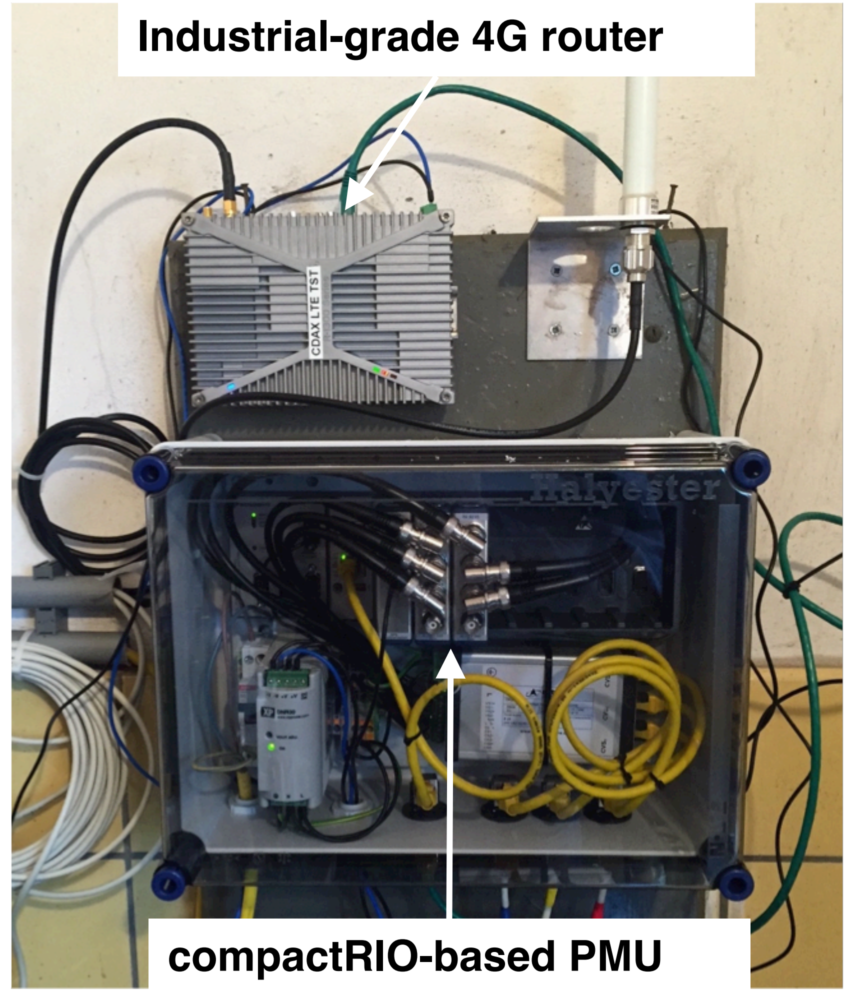
Phasor Measurement Units – The EPFL PMU

- First PMU worldwide **specifically designed for ADN** operating conditions
- Rugged and compact **NI-compactRIO** enclosure to fit in reduced spaces
- First worldwide **FPGA-based PMU** (high speed and determinism)
- Equipped with a ±100 ns (max error) stationary **GPS module**
- Metrologically characterized at **Swiss Federal Institute of Metrology** (METAS)
    - **Steady state accuracy**: 10 ppm (independently of harmonic distortion)
    - **Measurement reporting latency**: 37 ms
    - **Reporting rates**: 10-20-50-100-200 fps
    - IEEE Std. C37.118 **class-P compliant**

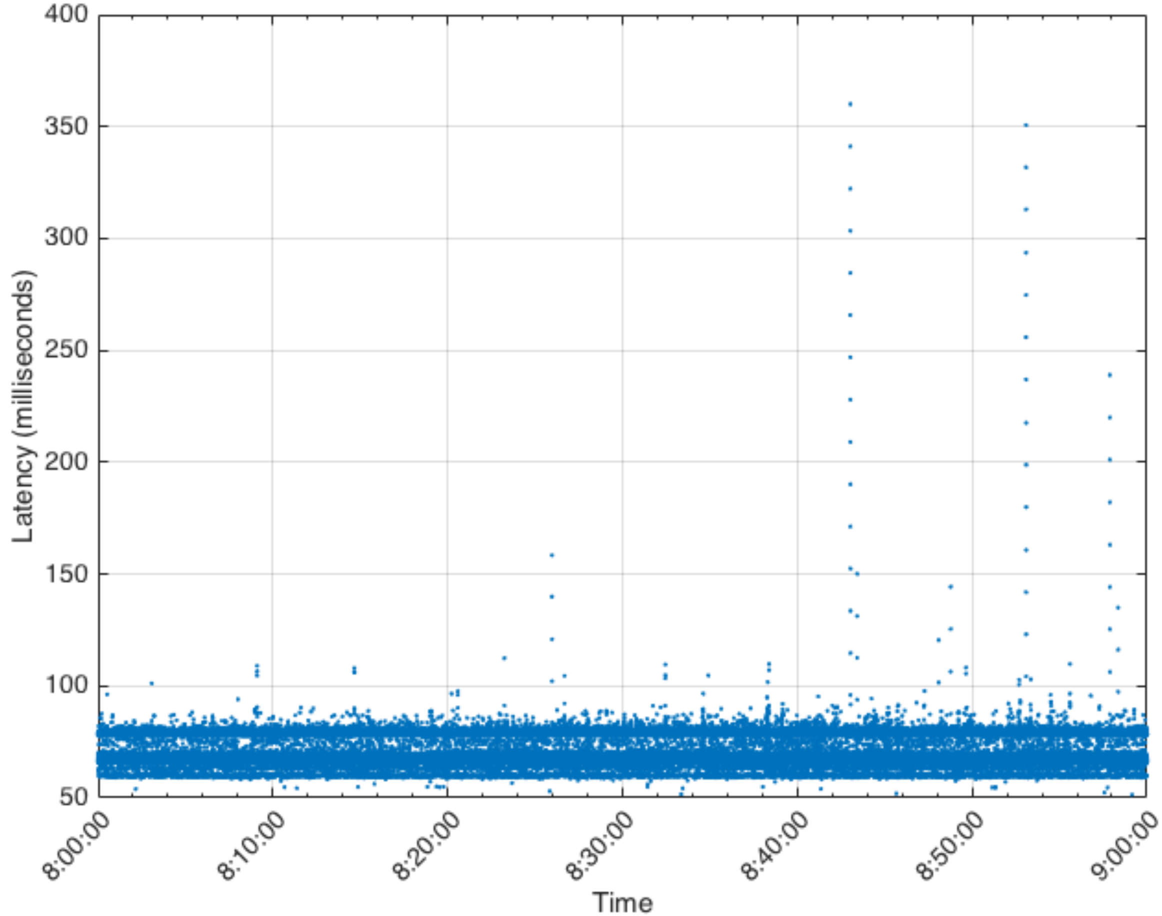


Substation setup



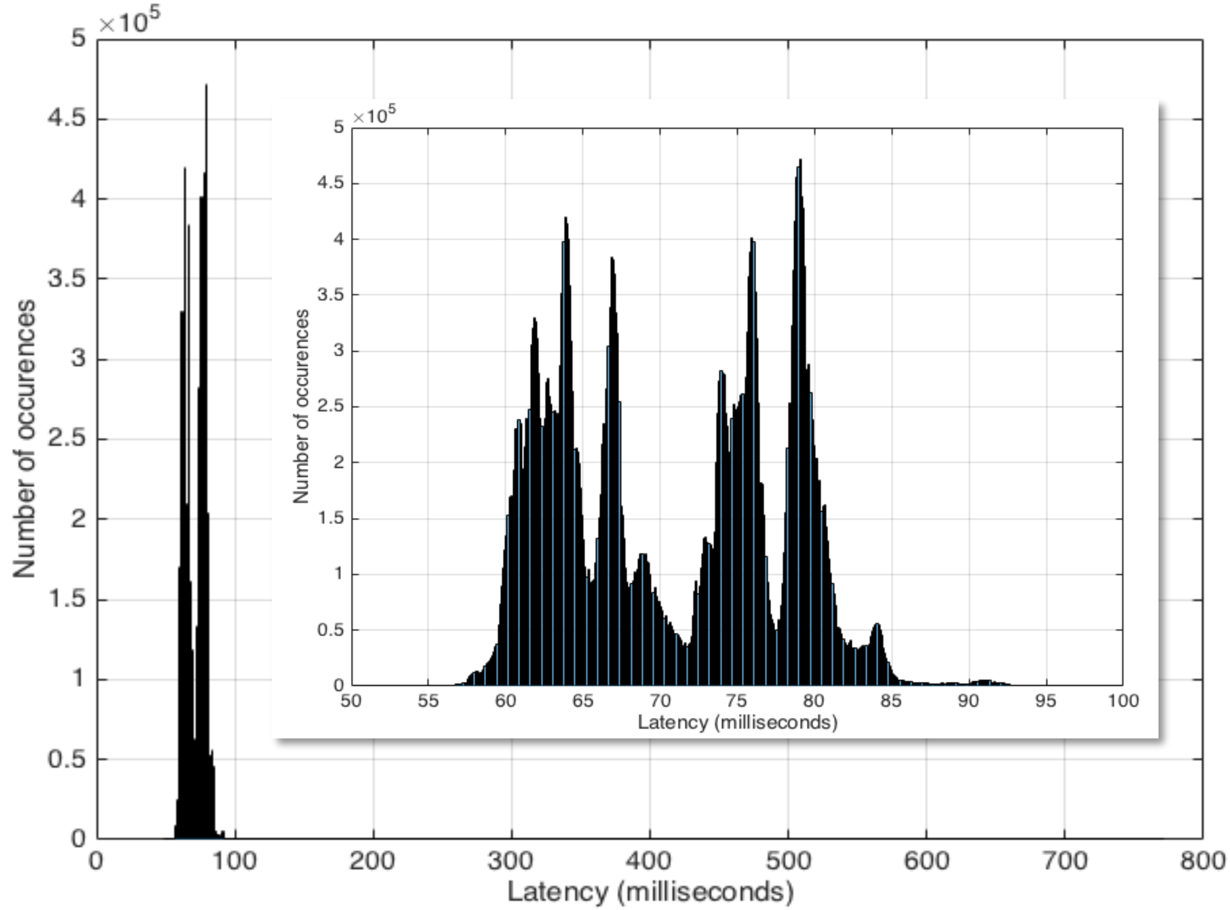


Synchrophasor data latencies (4G network)



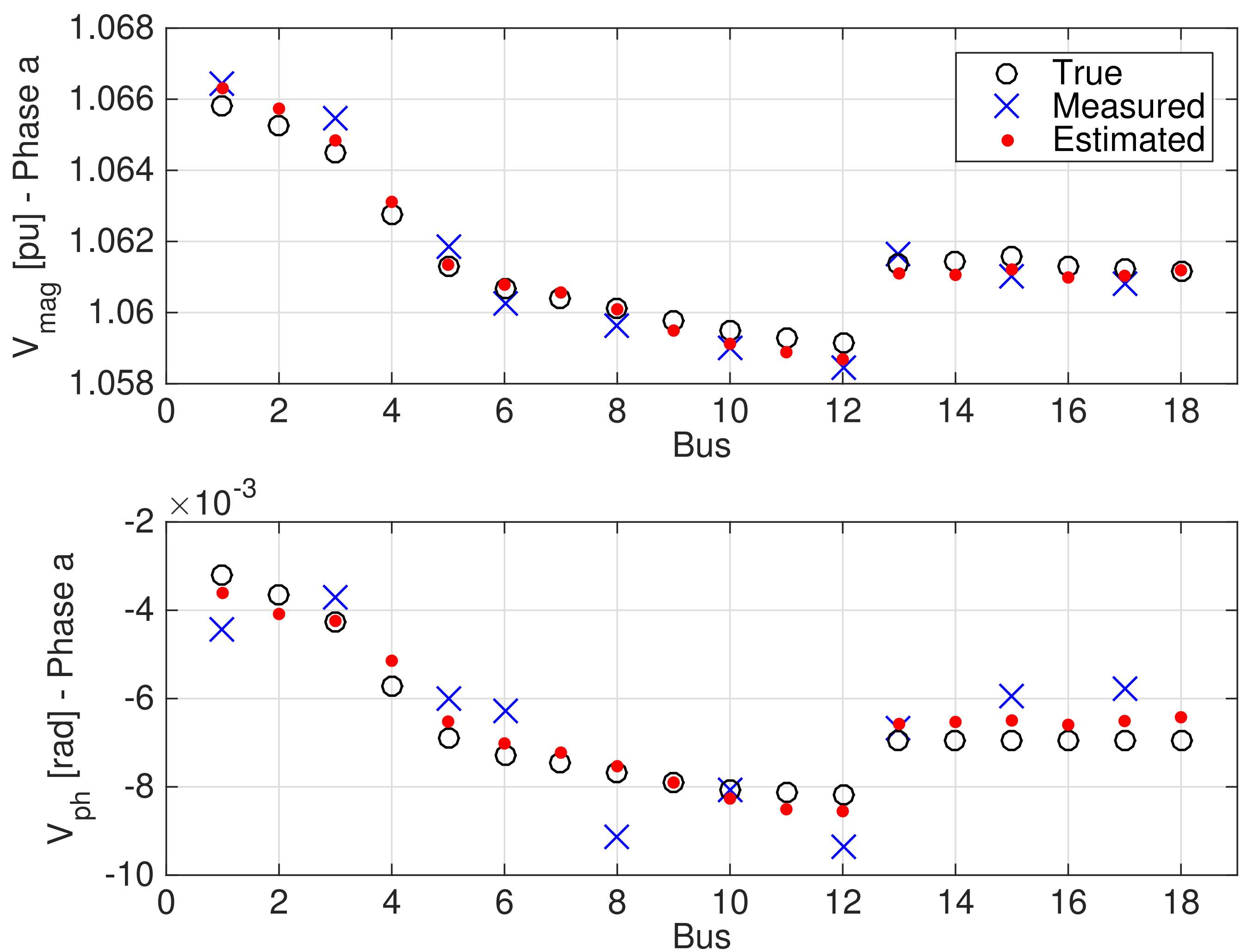
Mean	Stdev	Max	Min	Data Loss (%)
70.9 ms	8.1 ms	770.5 ms	49.2 ms	0.0053

Synchrophasor data latencies (4G network)



Mean	Stdev	Max	Min	Data Loss (%)
70.9 ms	8.1 ms	770.5 ms	49.2 ms	0.0053

Estimated vs measured voltage profiles



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
- Flexible data communications platform w/ C-DAX middleware

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

- What's next?
  - 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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