

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, 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>

Algorithms and communications for smart grids: 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

Distributed generation (large scale)
Green energy sources (fluctuating)

ICT infrastructure

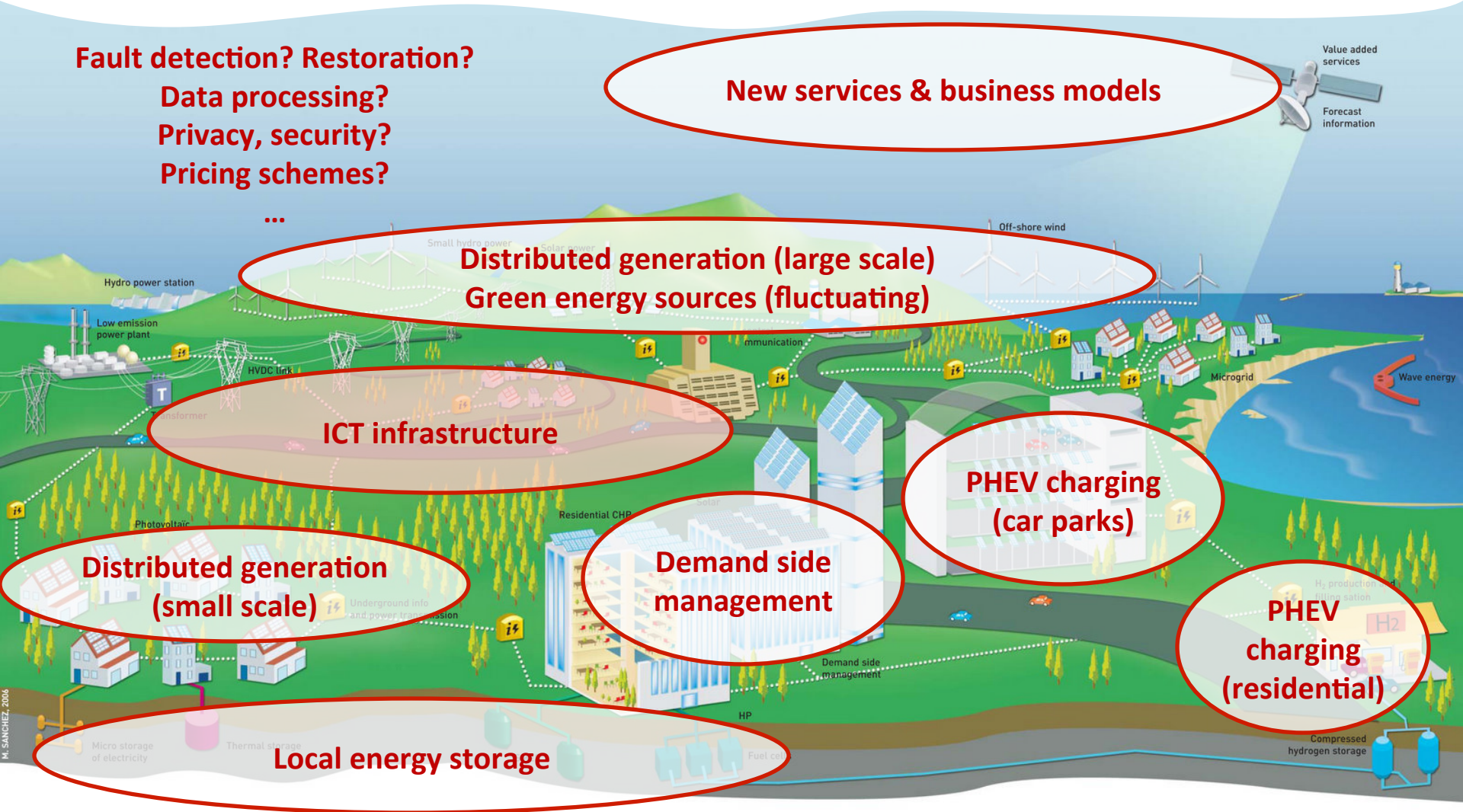
Distributed generation (small scale)

Demand side management

PHEV charging (car parks)

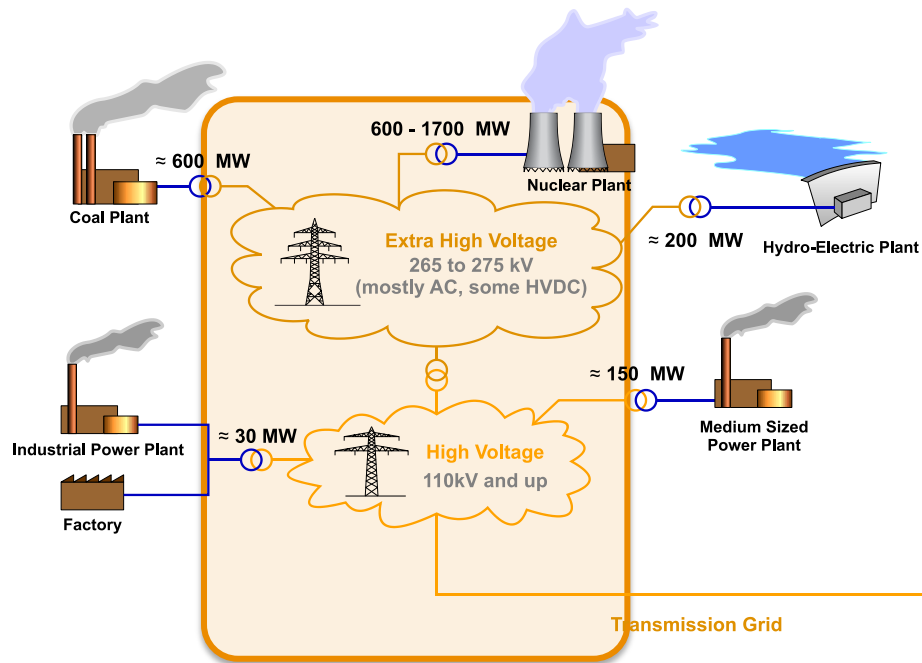
PHEV charging (residential)

Local energy storage

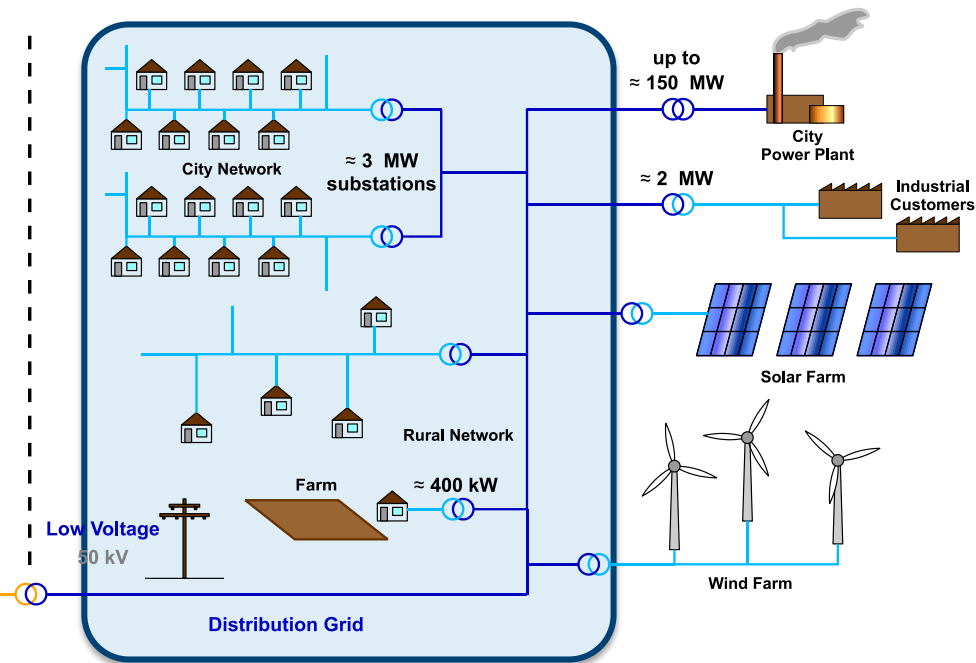


Power grid structure

Transmission network (operated by TSO)



Distribution network (operated by DSO)



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

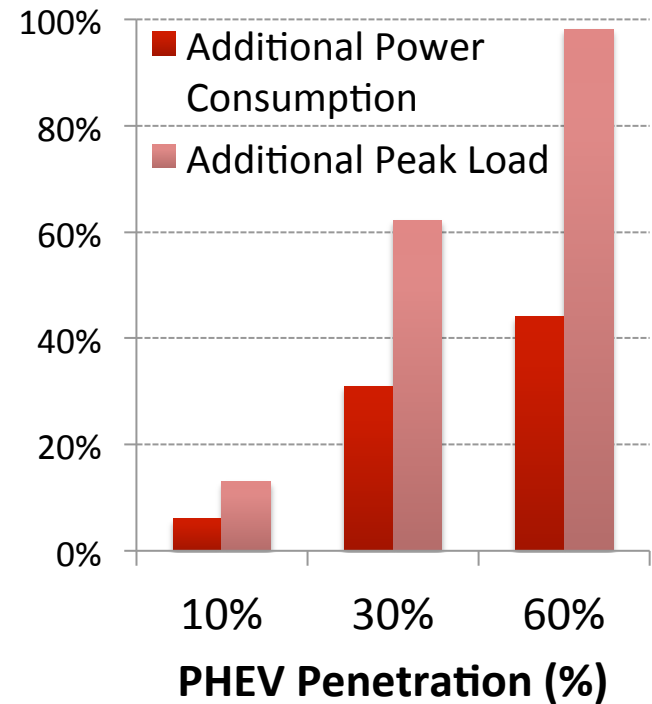
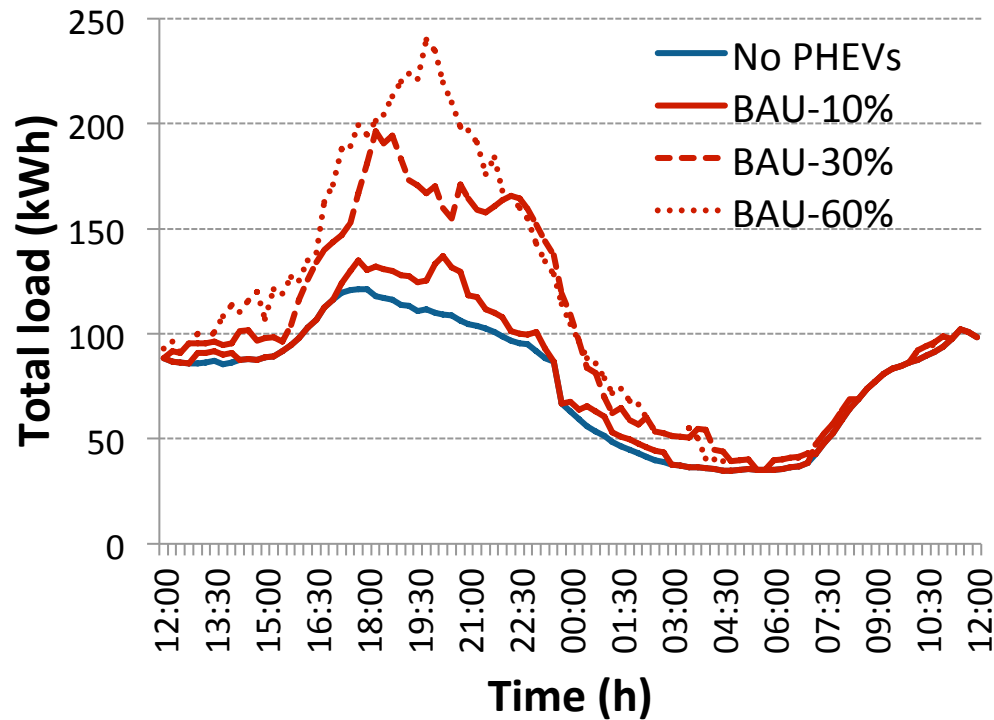
■ Research questions:

1. Impact of (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

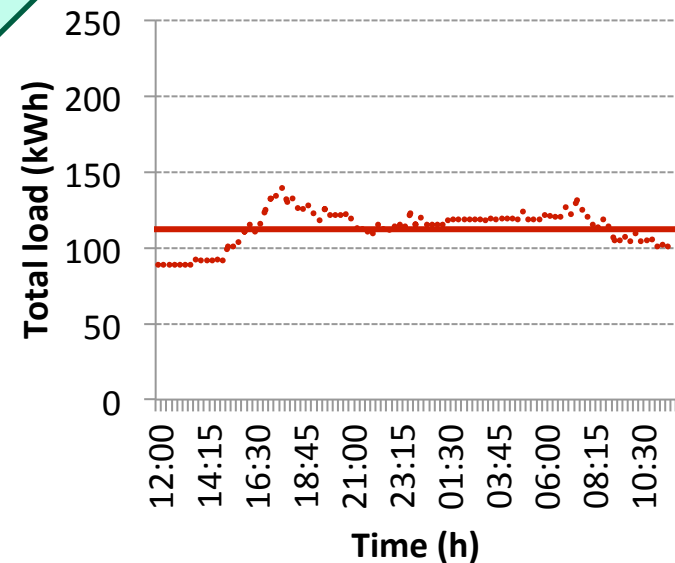
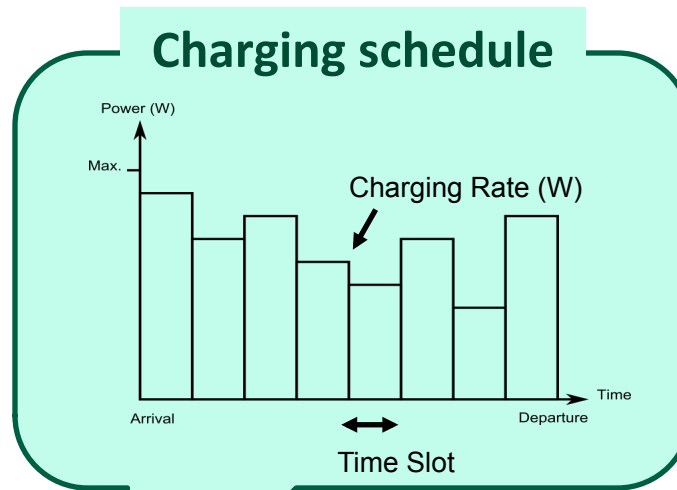
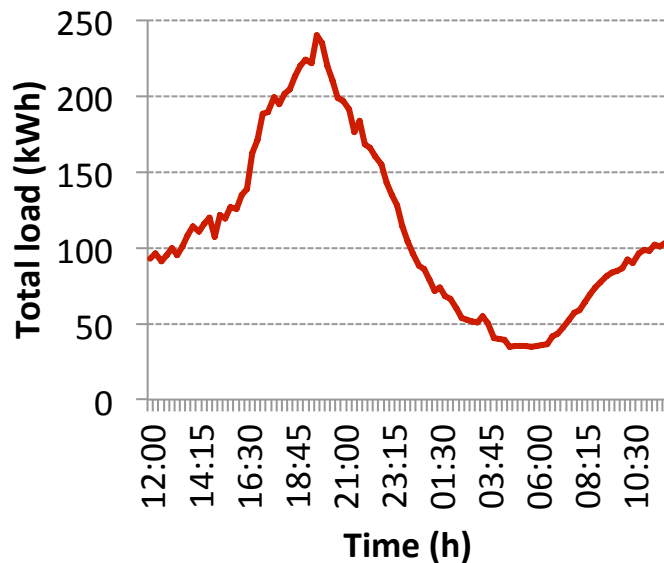
- Sample analysis for 150 homes, x% of them own a PHEV
- BAU = maximally charge upon arrival at home



Controlling EV charging?

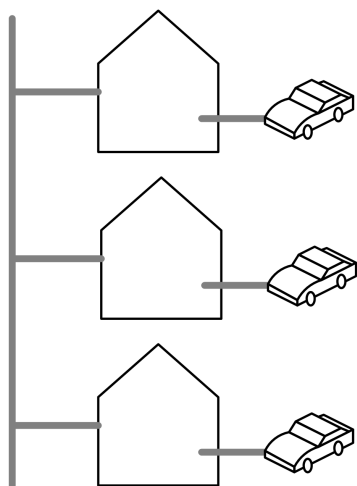
Objectives:

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



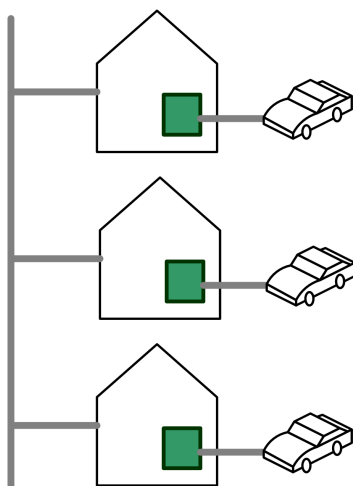
Smart charging: QP

BAU
(uncontrolled)



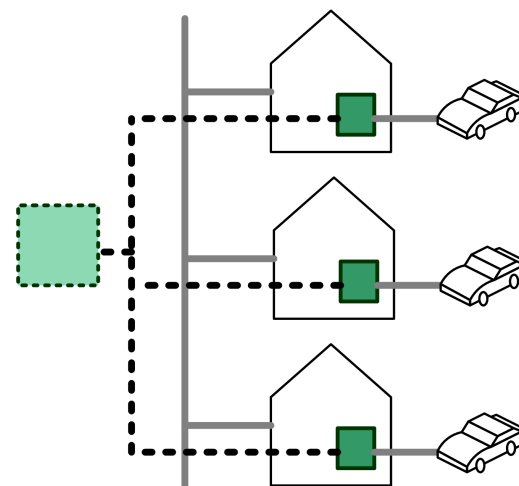
(a)

Local control (QP)



(b)

**Global control (QP),
Market MAS**



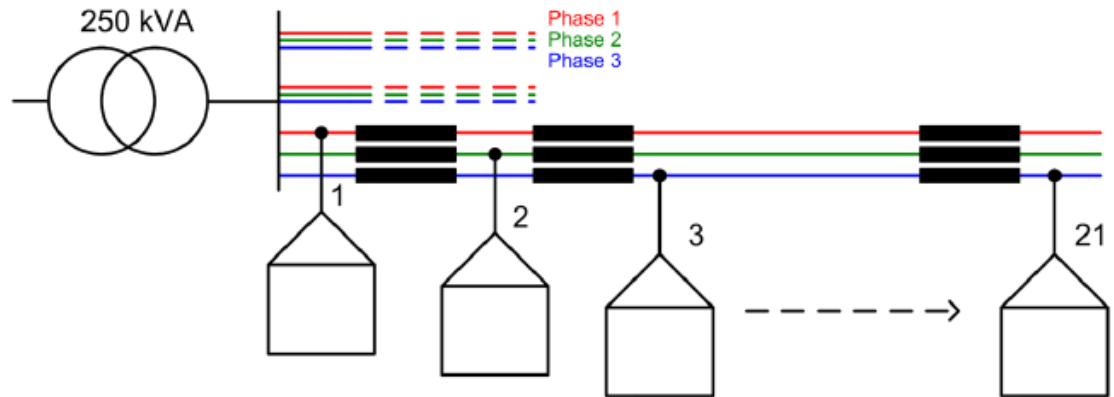
(c)

— Power line - - - Communication network ■ Home energy box □ Global energy controller

Case study

■ 63 Households

- Randomly distributed over 3 phases
- Spread over 3 feeders

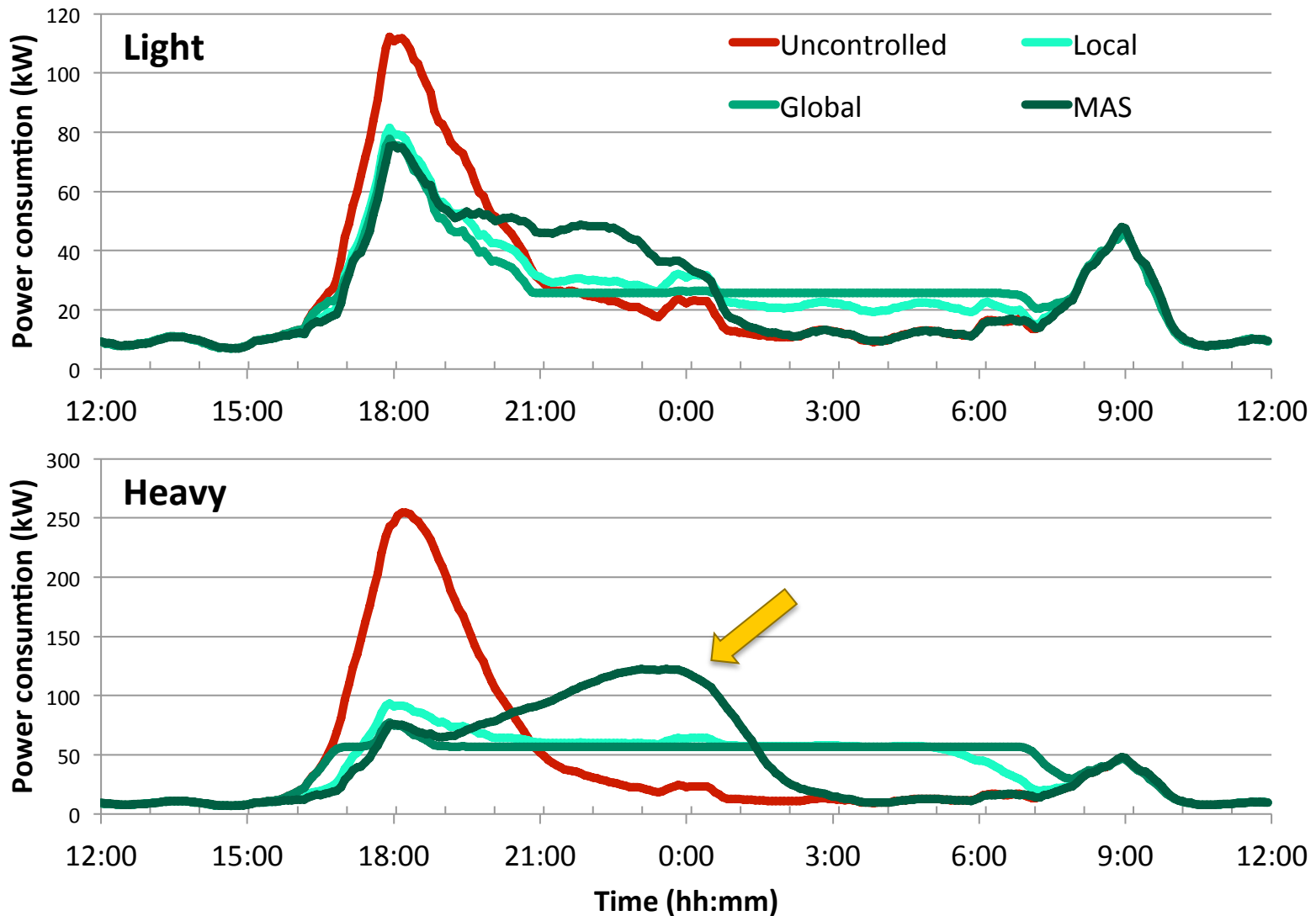


■ Electrical vehicles

- 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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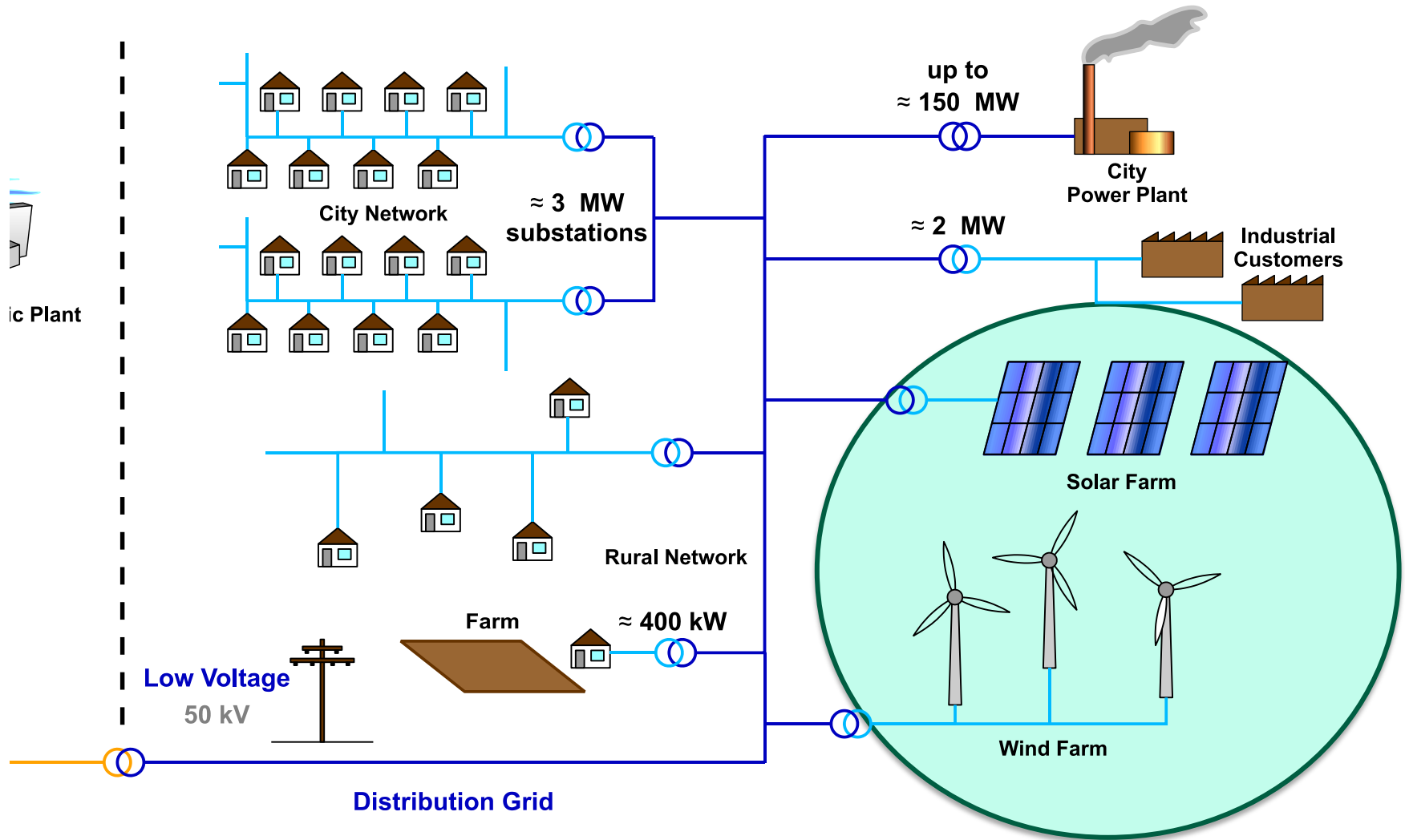
6. EV usage analysis

Part III: Communication middleware

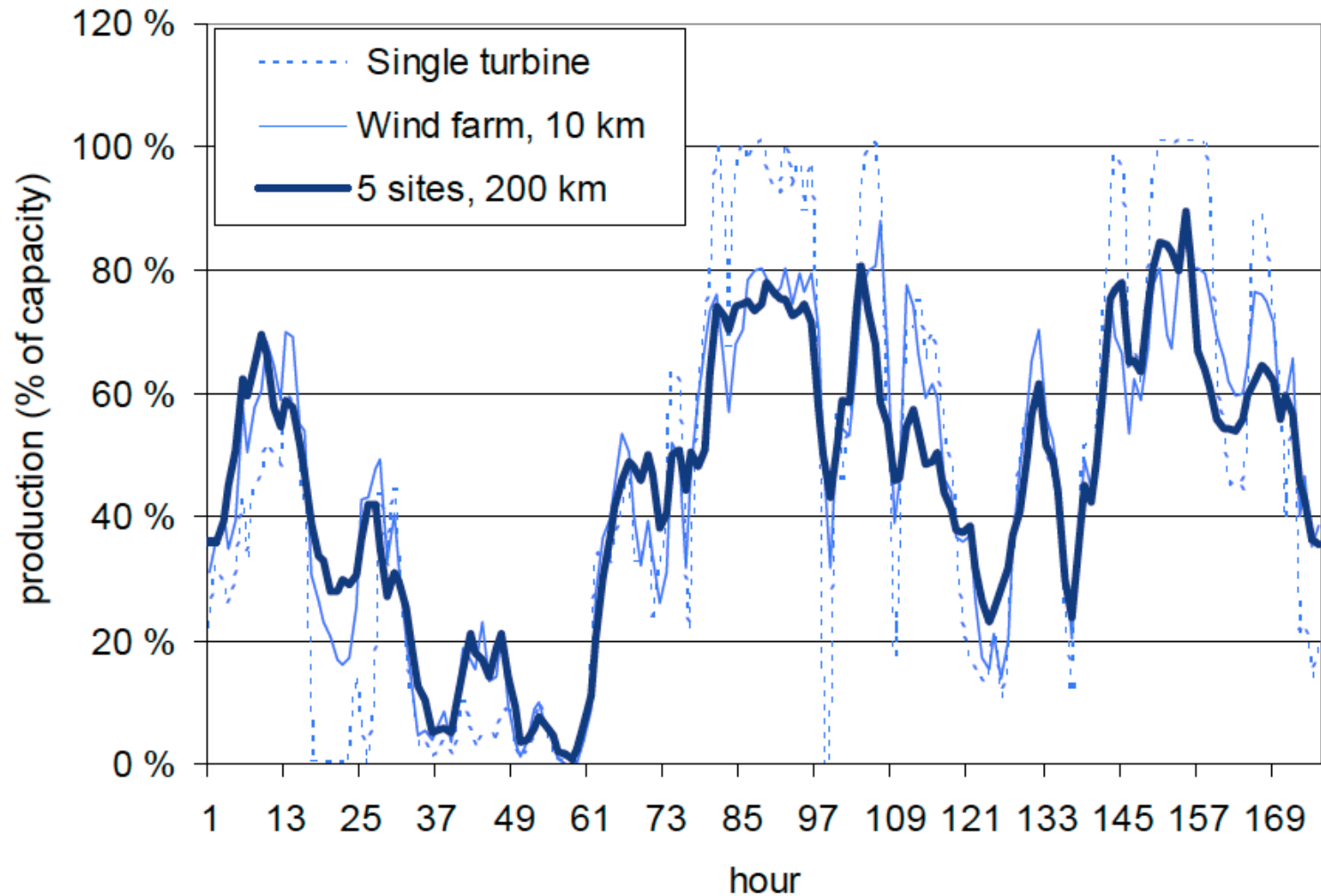
7. C-DAX: A cyber-secure data and control cloud for power grids

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

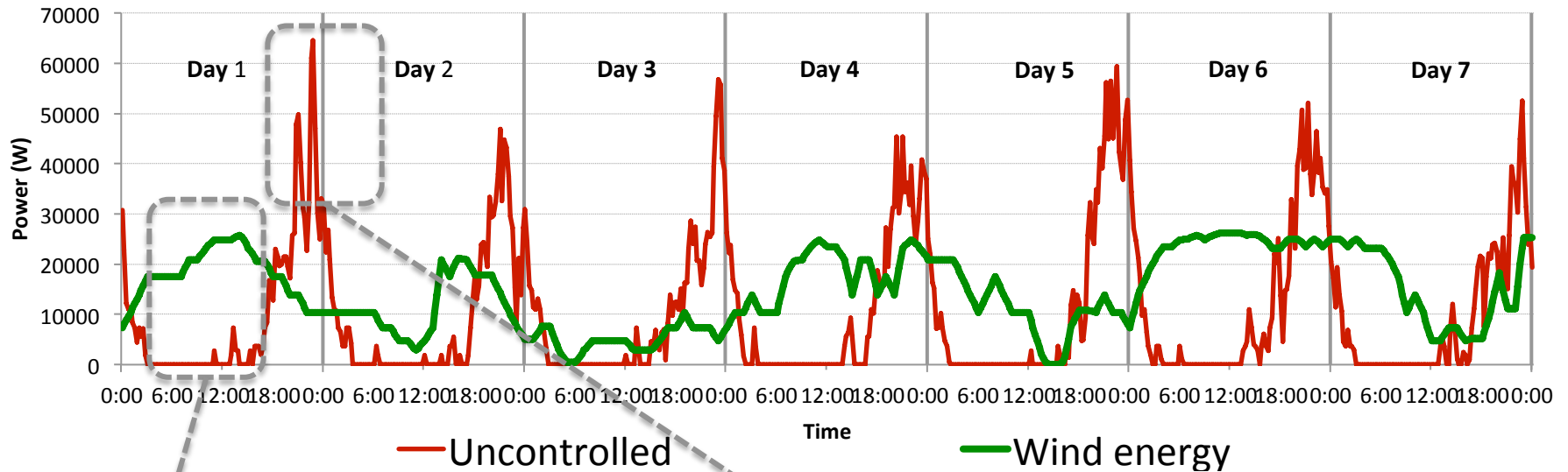
Distributed generation (DG)



A typical wind profile



Wind balancing with EV charging

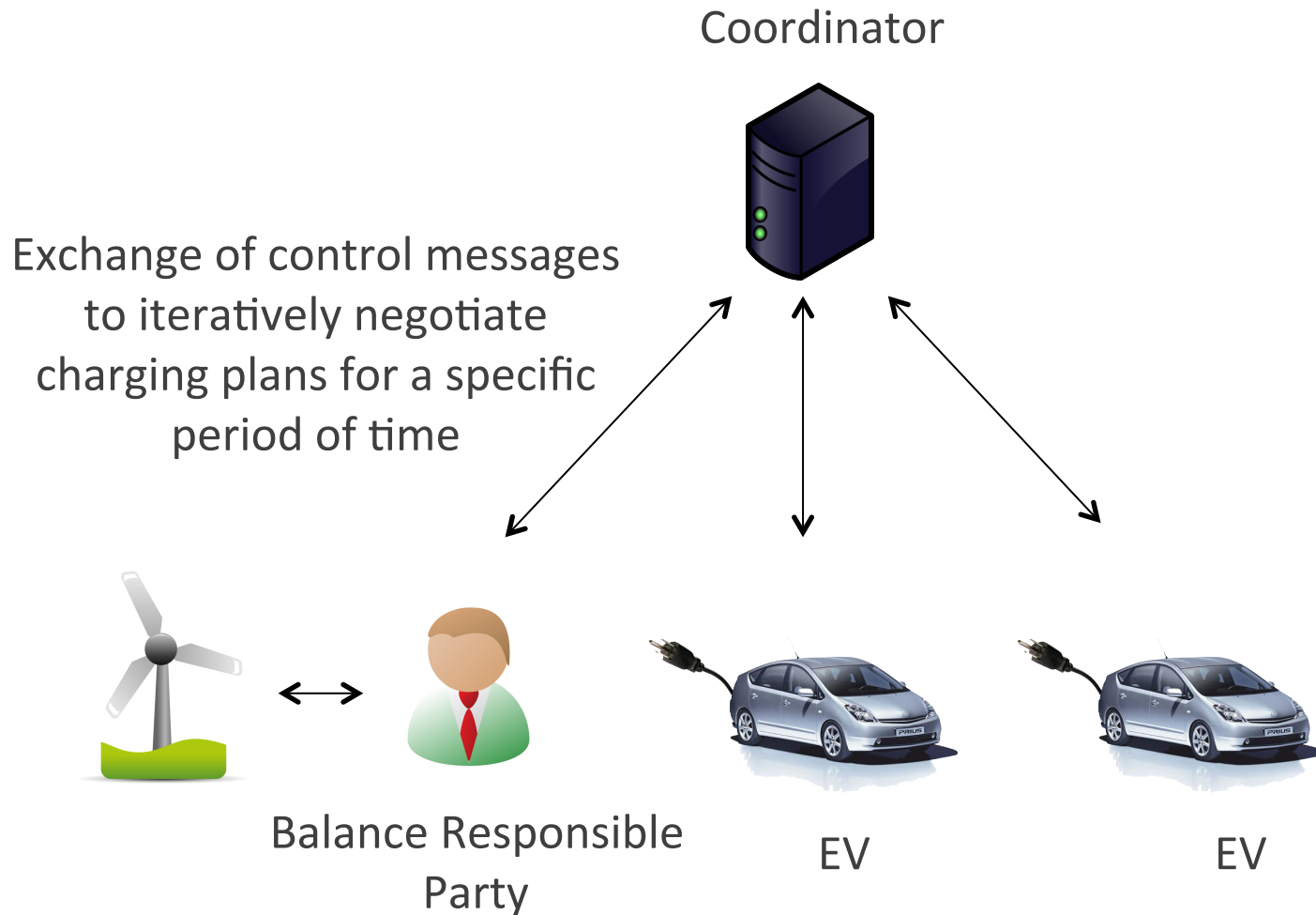


Supply/demand imbalance & High peak loads

- 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:

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

- 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

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

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

1 BRP
problem

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

K subscriber
problems

- Iteratively update pricing vector $\lambda_t \dots$

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:** $d^i = [d_1^i, d_2^i, \dots, d_T^i]$
 - **EVs:** $x^{k,i} = [x_1^{k,i}, x_2^{k,i}, \dots, x_T^{k,i}]$
 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

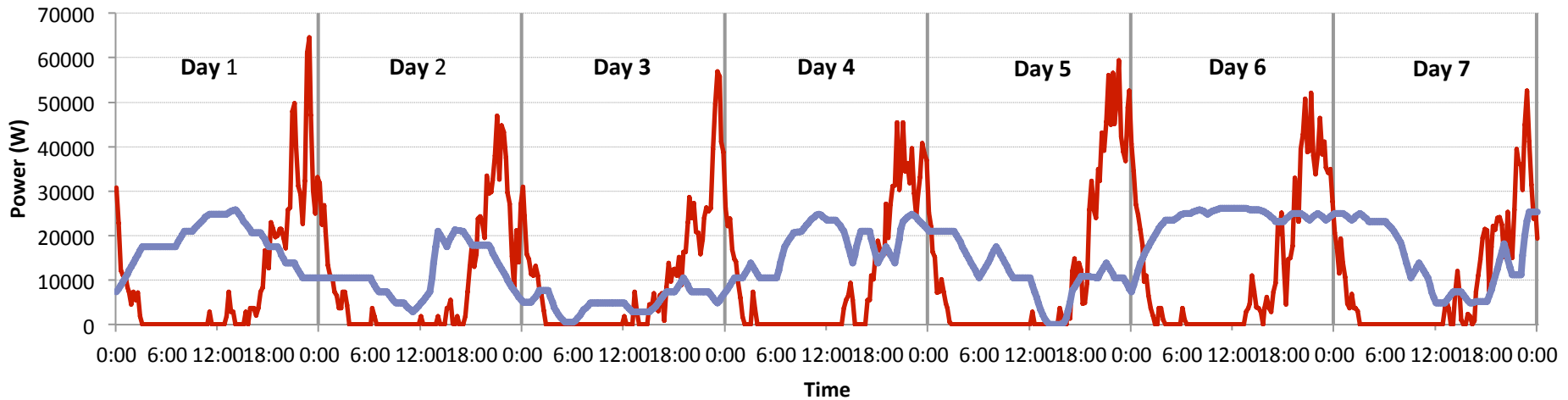
■ “Ideal world” benchmark

- Offline all-knowing algorithm determines schedules for ALL sessions
- No EV disutility function → maximum flexibility

- Objective:

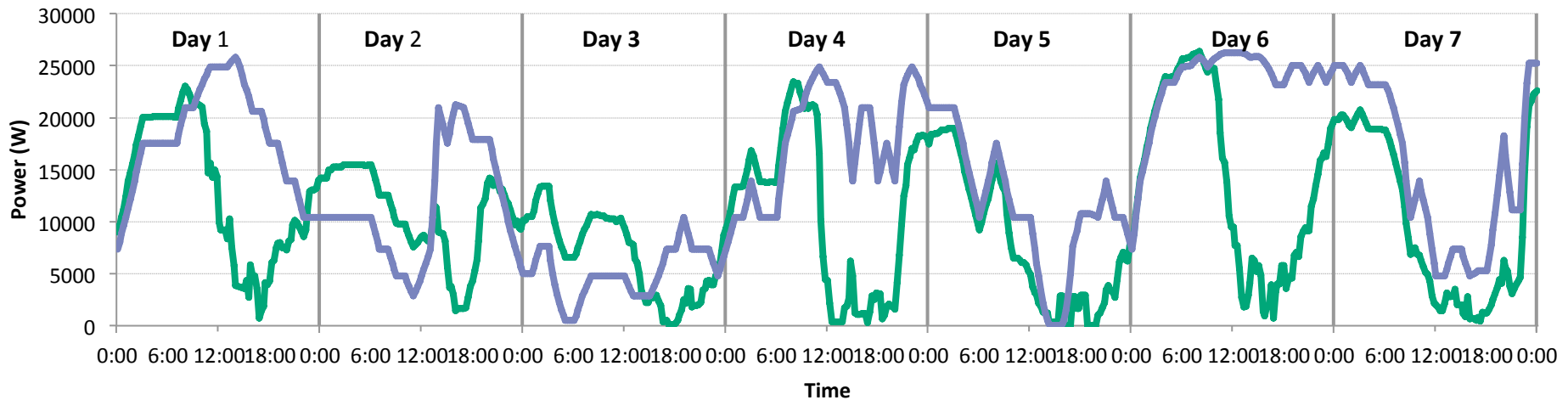
$$\min \sum_{t=1}^S \left(w_t - \sum_{k=1}^K x_t^k \right)^2$$

Results: Uncontrolled BAU vs. Distributed



— Uncontrolled

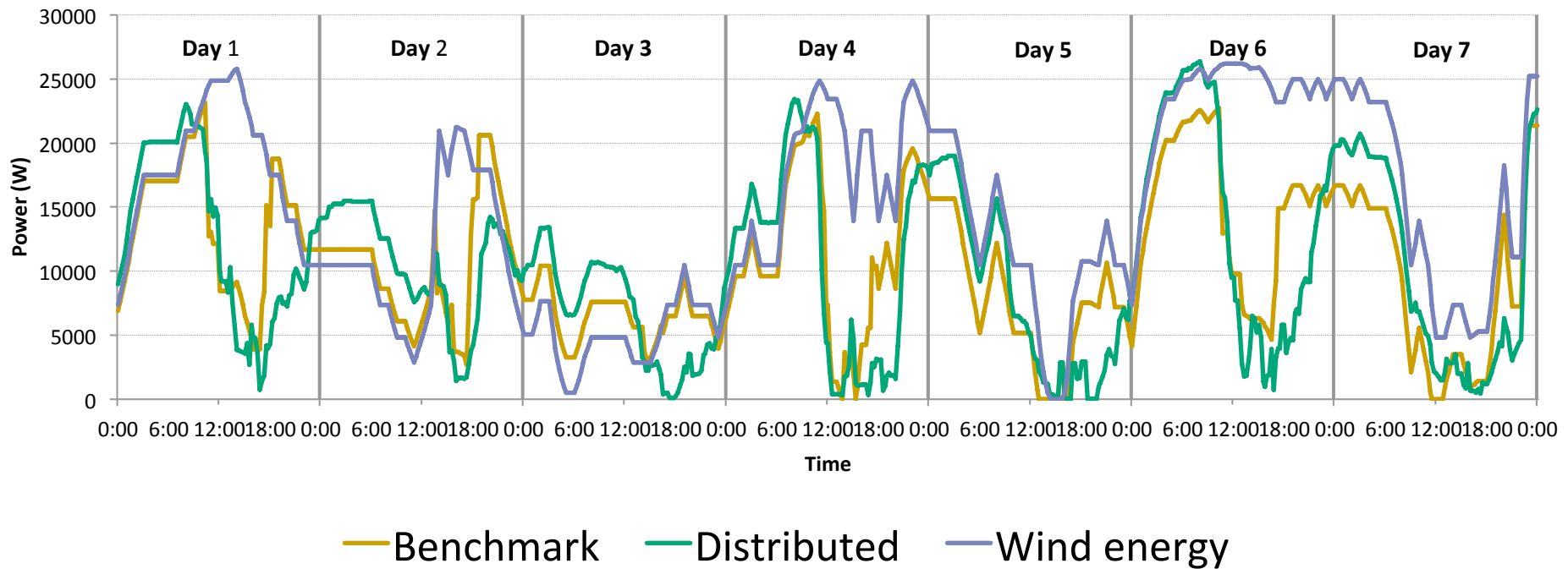
— Wind energy



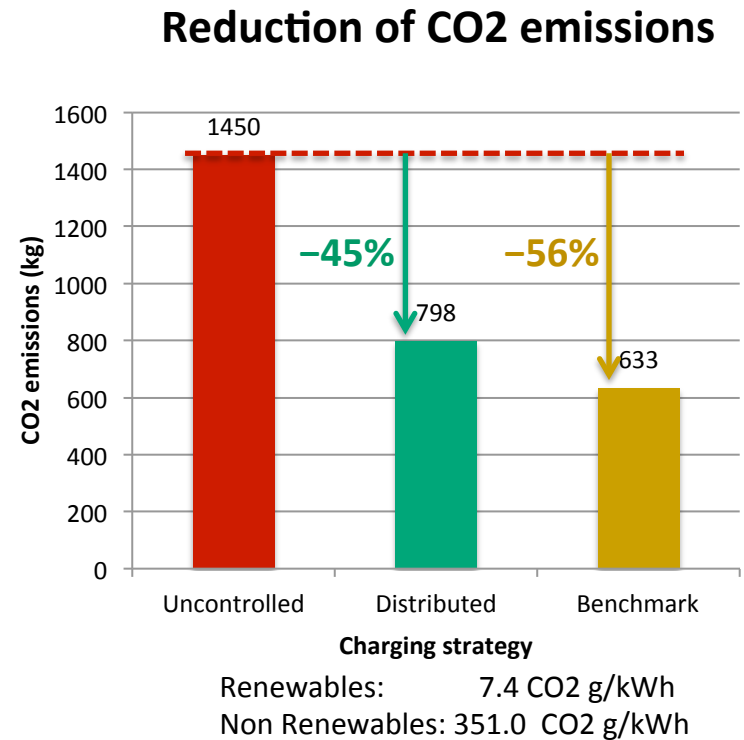
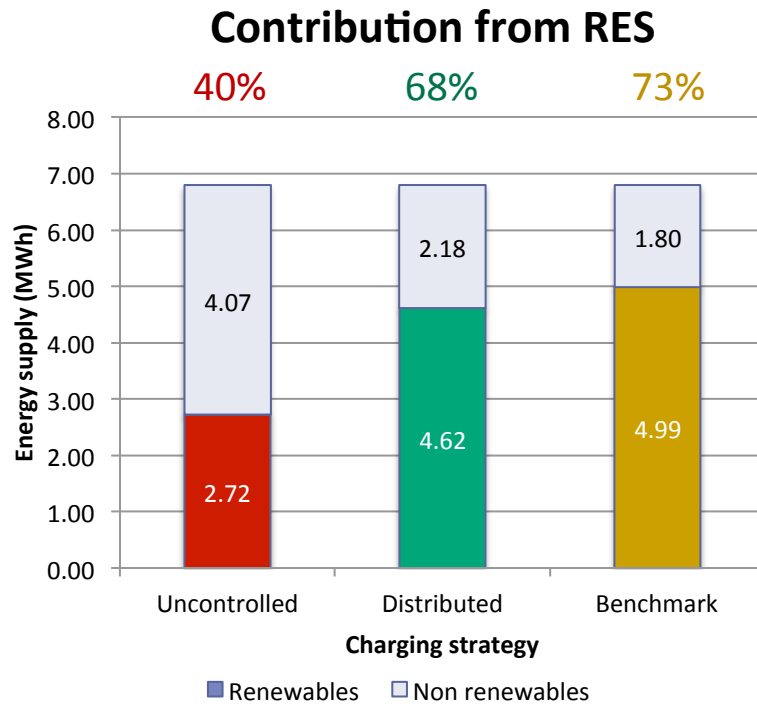
— Distributed

— Wind energy

Results: Distributed vs. Benchmark



Results: Energy Mix



- Total energy consumption \approx 6.8 MWh
- Substantial increase in the use of renewable energy
- Reduced CO₂ 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 CO₂ emissions

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

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

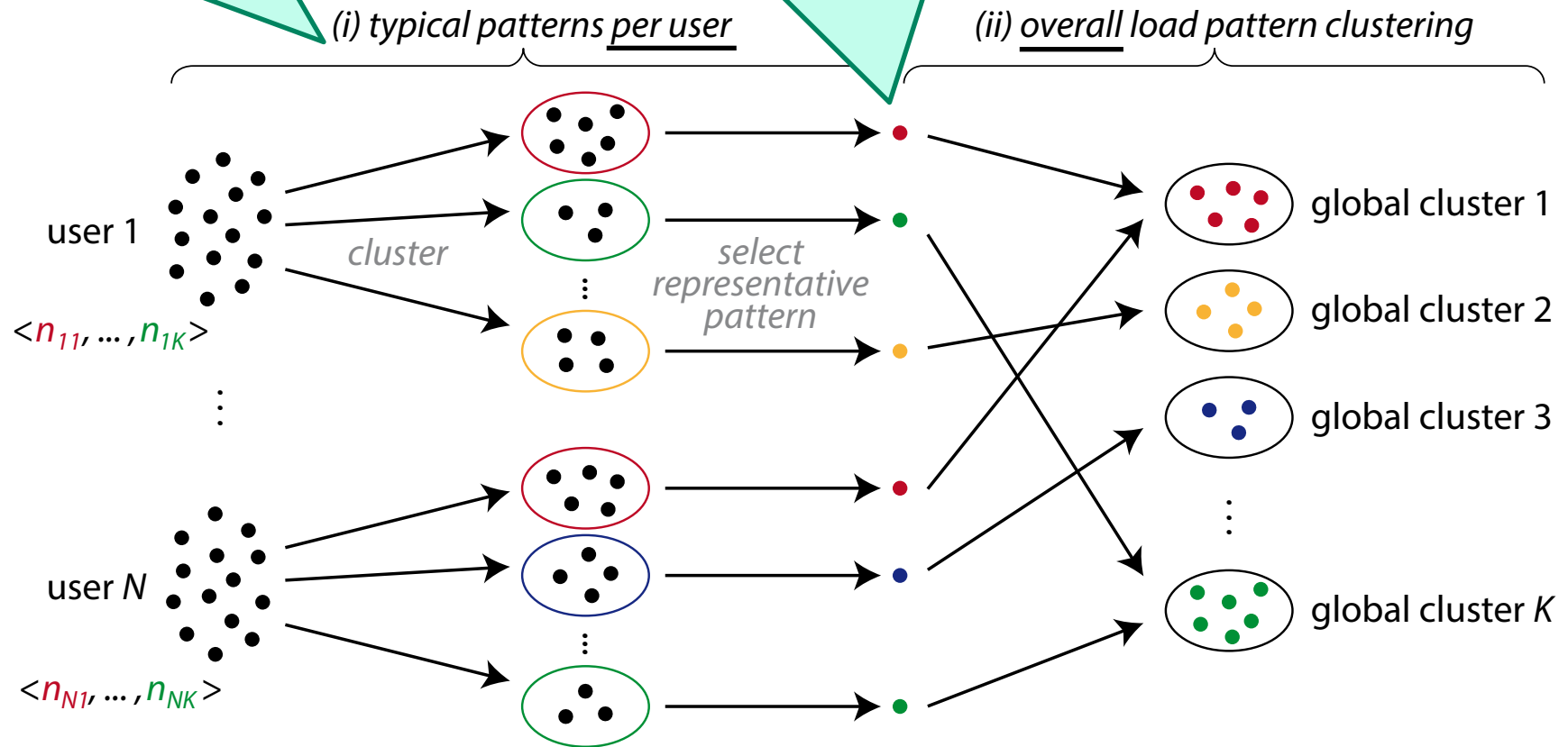
- **Goal:** Identify different types of daily power consumption time series
 1. Single household: distinct types of daily load patterns?
 2. Over whole population: distinct groups of users?

- **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



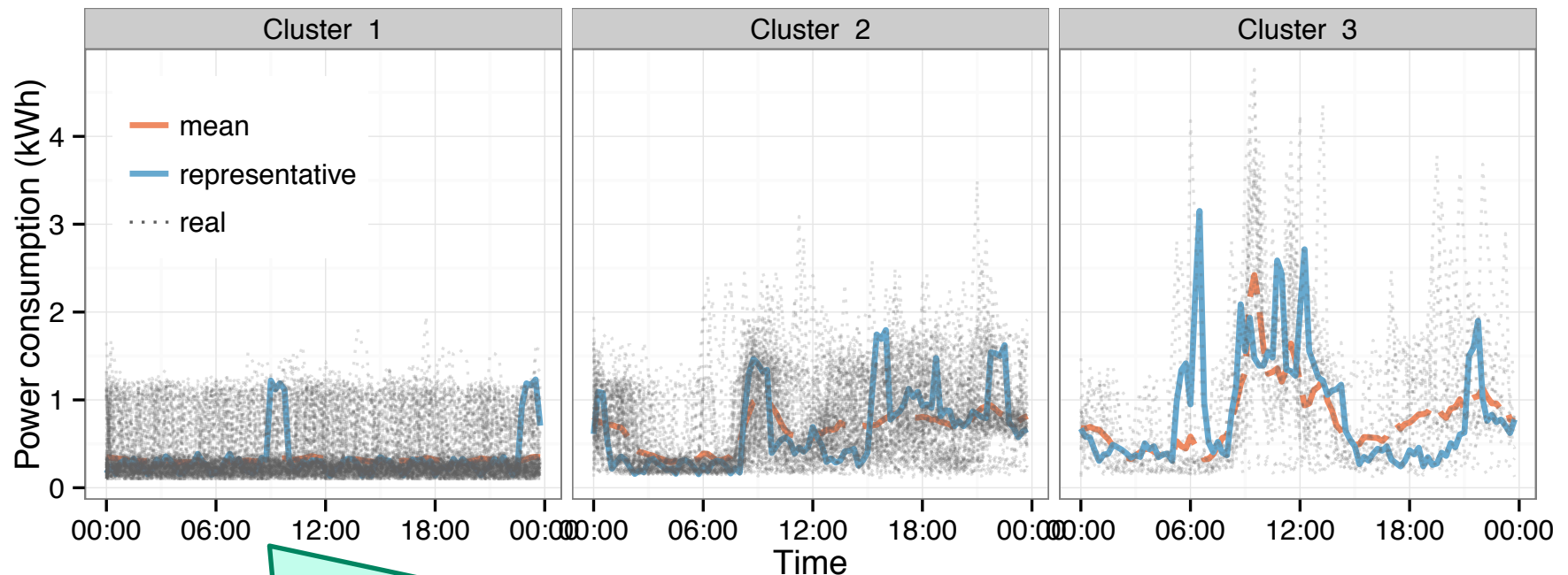
- G-means (instead of k-means) [Hamerly2003]

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

Sample result: Single user

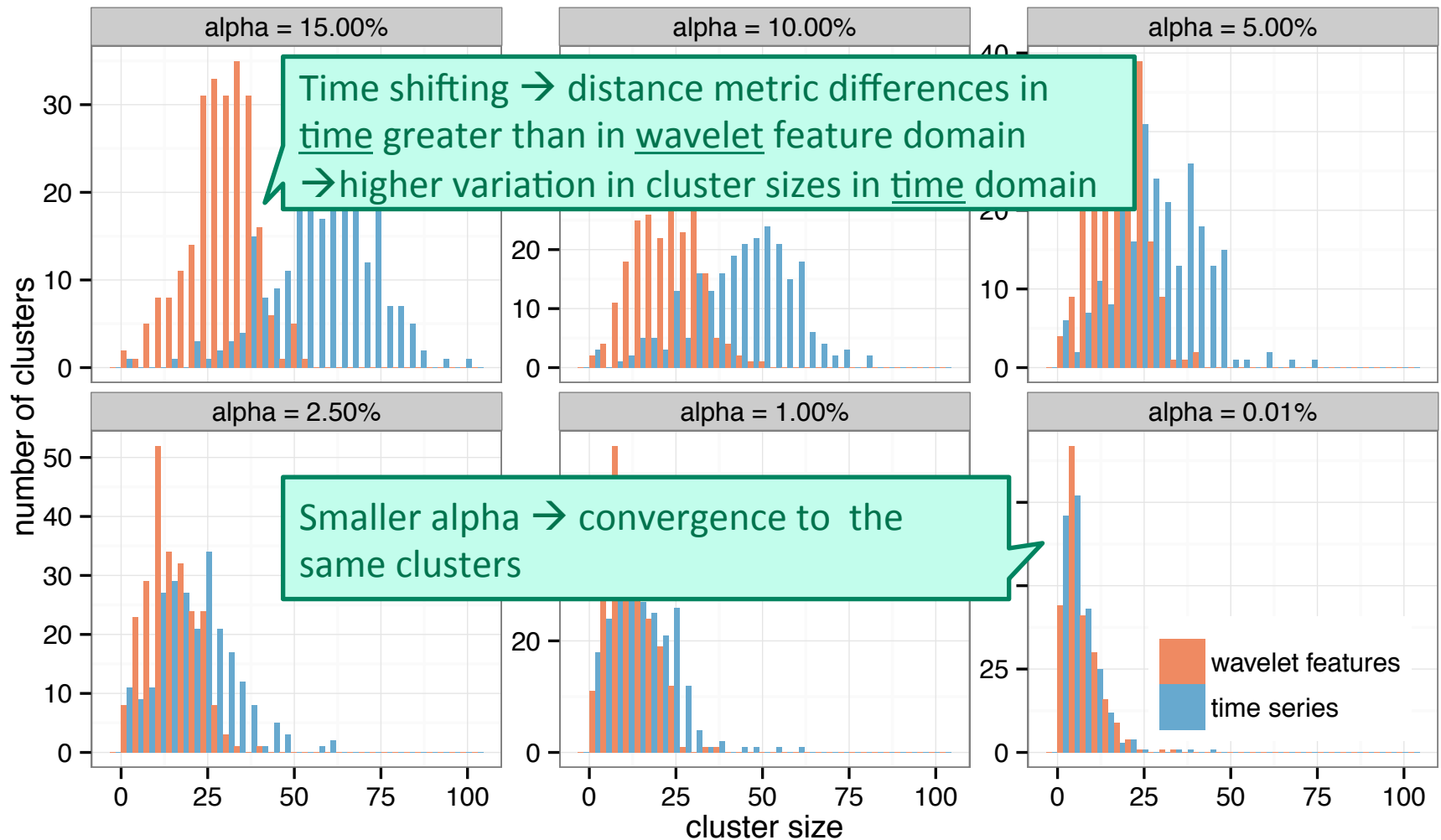
For $\alpha = 0.01\%$ \rightarrow low number of clusters

Note: representative \neq 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 \rightarrow 7 or 8 features)

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

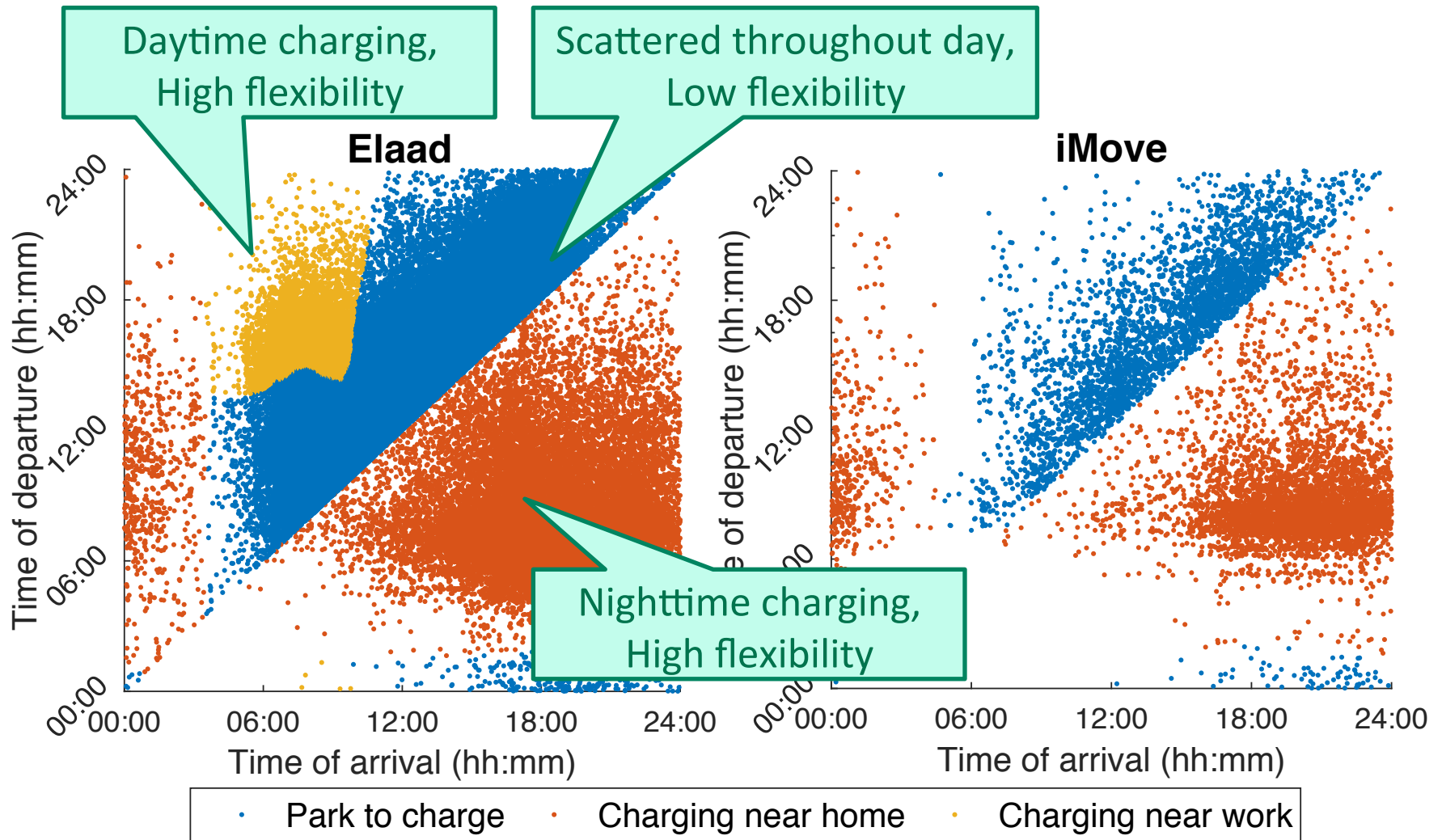
Input: Two real-world data sets

	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 card.

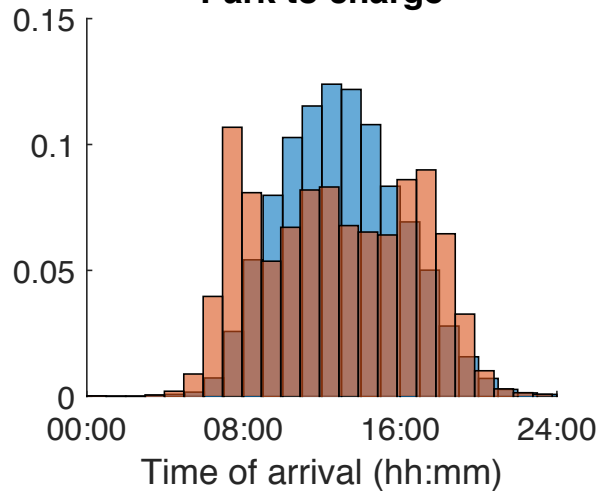
User behavior: 3 Types of behavior



User behavior: Distributions of *arrival times*

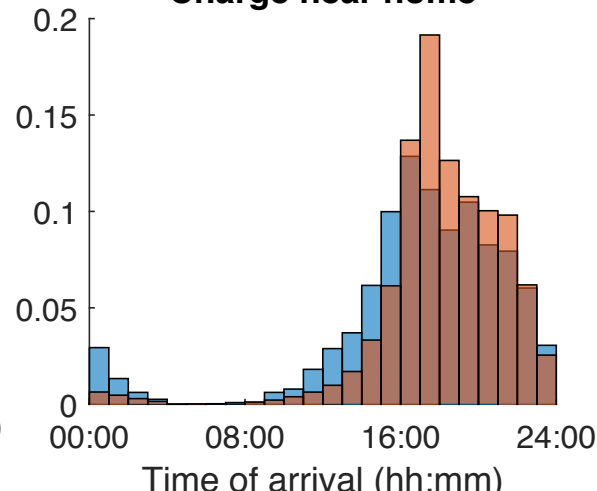
Different week vs weekend pattern

Park to charge



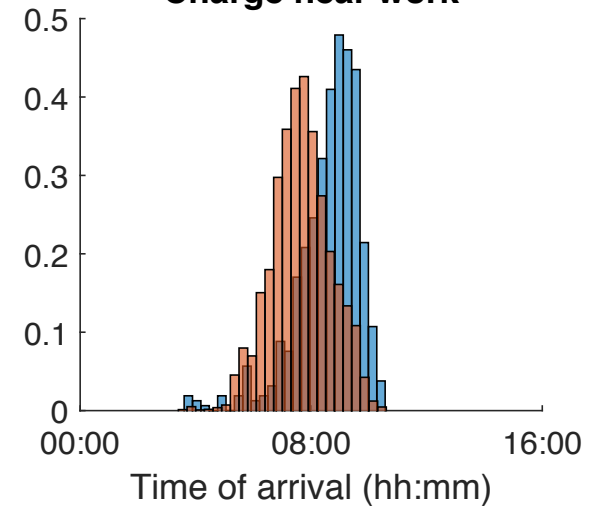
Slightly more spread in weekend

Charge near home



Shift to later times in weekend

Charge near work

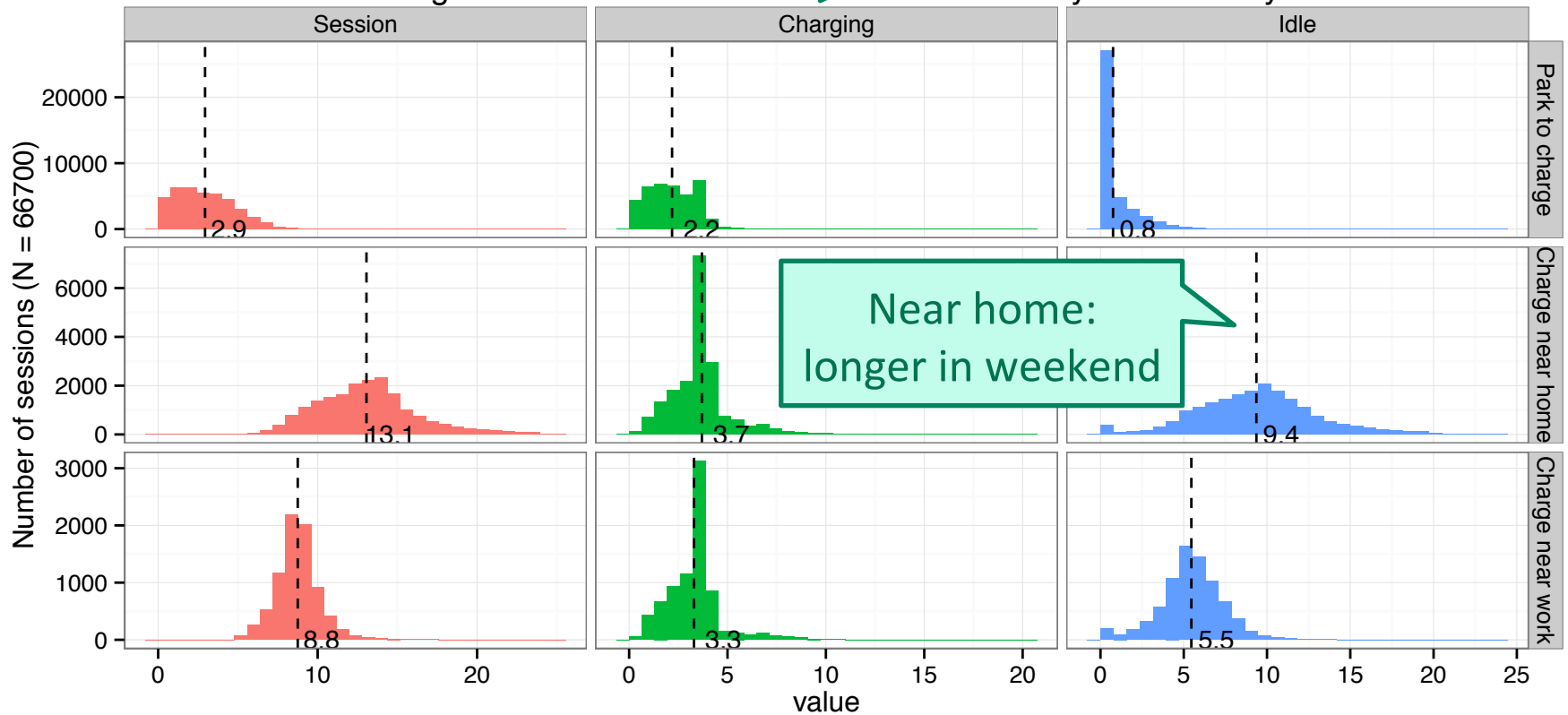


Weekends Weekdays

User behavior: *Session* duration – Weekdays

Charging duration:
Week \approx weekend

Histogram of duration for sessions less than 1 day -- Weekdays

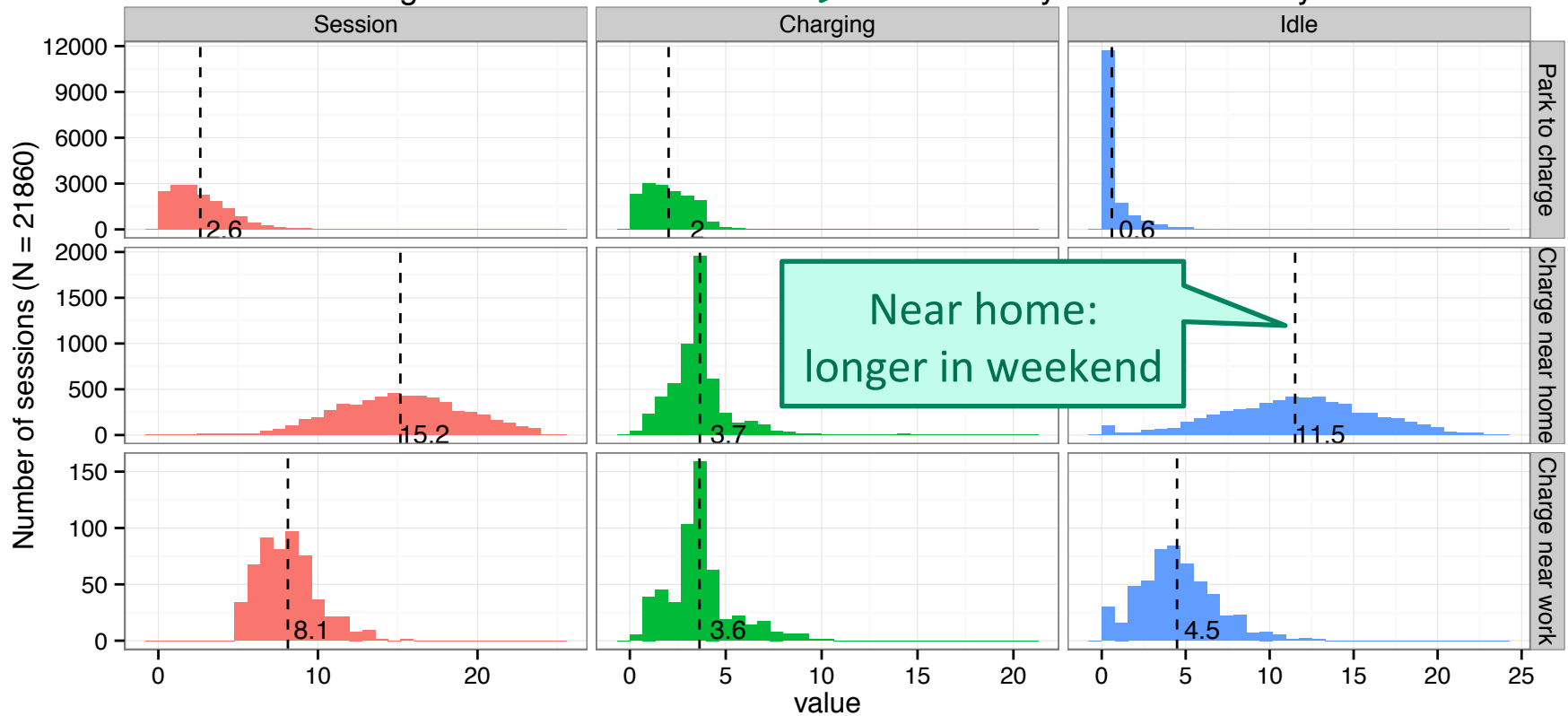


Near home:
longer in weekend

User behavior: *Session* duration – Weekends

Charging duration:
Week \approx weekend

Histogram of duration for sessions less than 1 day -- Weekend days



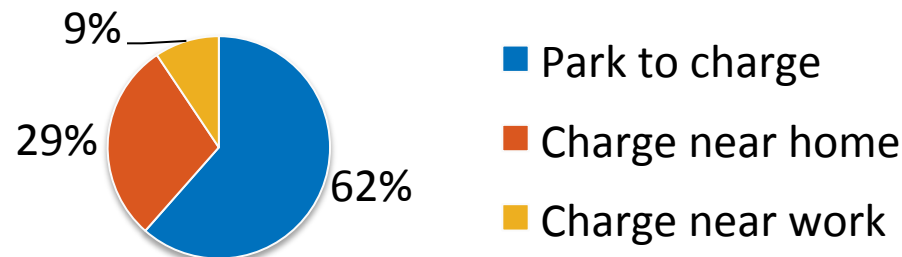
Near home:
longer in weekend

User behavior: Statistical models

Table II: Fitted distributions for total sojourn and idle times

Cluster	Sub-cluster departures	Fraction	Sojourn time (δ^{sojourn})			Idle time (δ^{idle})		
			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 $\delta_{\text{normalized}} = \frac{\delta - \min}{\max - \min}$.



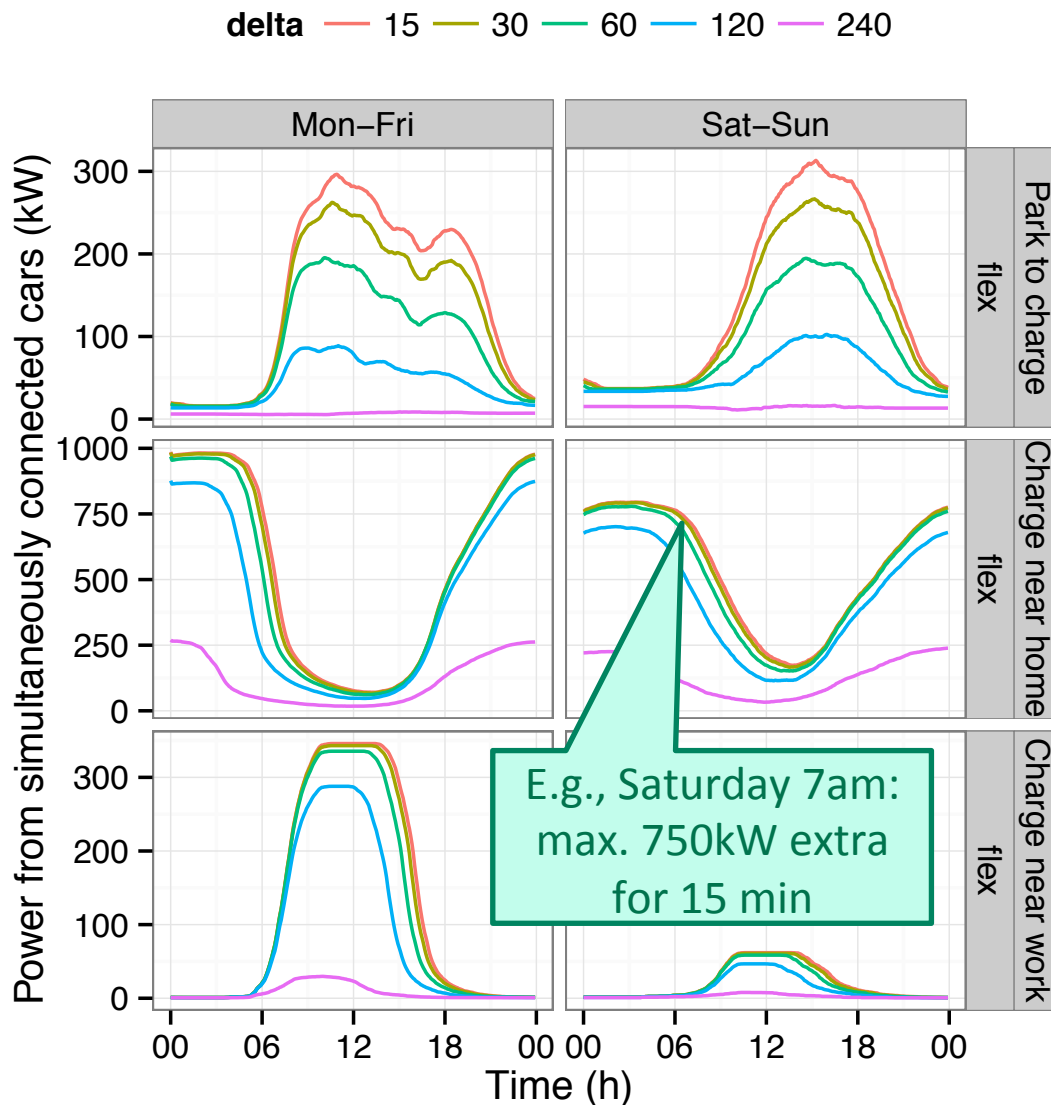
Quantification of flexibility: Calculation

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

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

- Charging session has to include $[t, t+\Delta]$
- Charging duration $\geq \Delta$ [else we could not consume in full interval]
- Flexibility = session duration - $\Delta \geq$ charging duration [we can move it away]

Quantification of flexibility: Result



- Park to charge:
 - Daytime flexibility
 - Weekend: \approx volume, but \neq 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, noon in weekend => can have ~7MW extra for 2h

PS: Similar analysis for household appliances in smart device trial:

N. Sadeghianpourhamami, T. Demeester, D.F. Benoit, M. Strobbe and C. Develder, "Modeling and analysis of residential flexibility: Timing of white good usage", Appl. Energy, Jul. 2016, pp. 1-27. (Accepted for publication)

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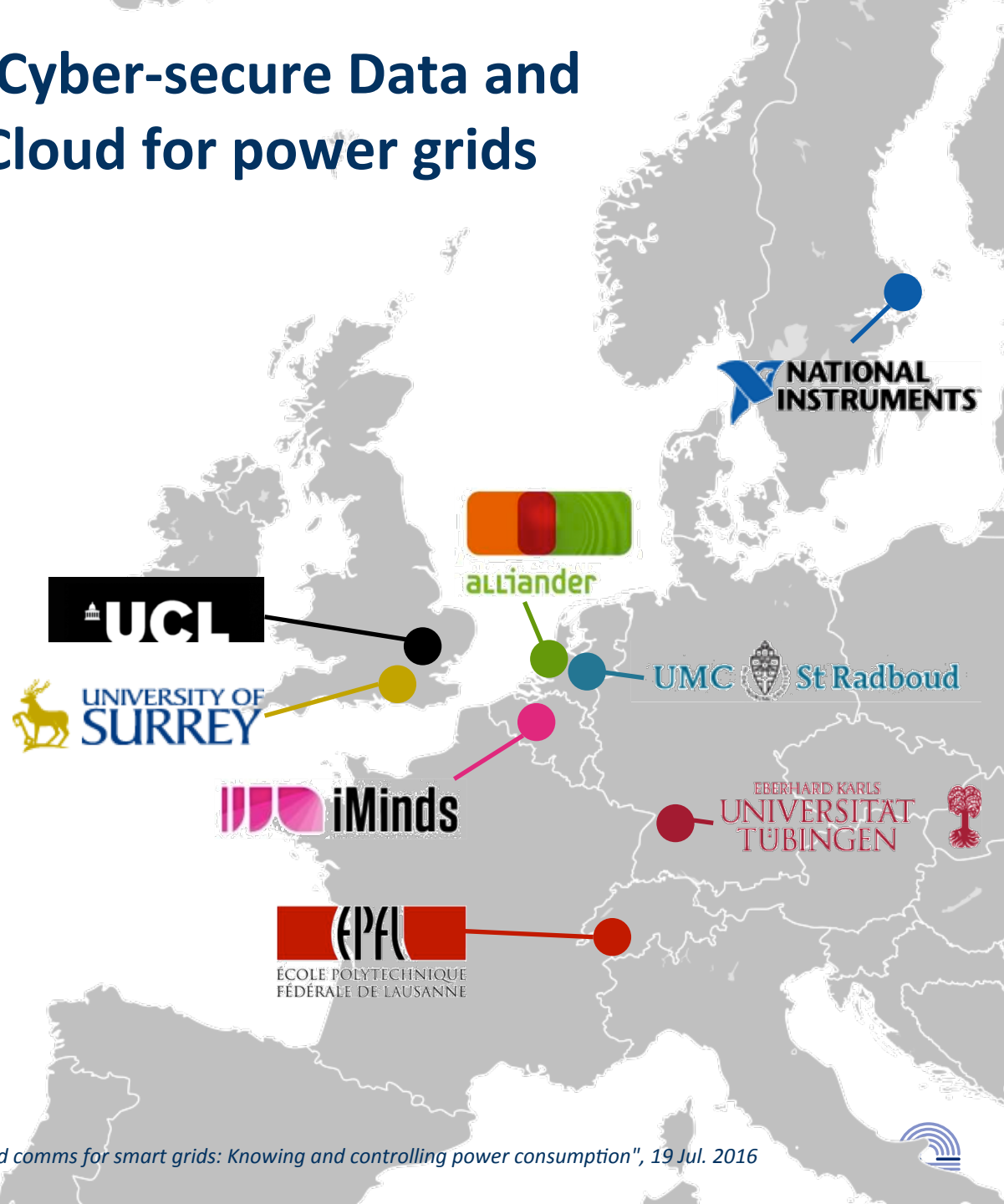
7. C-DAX: A cyber-secure data and control cloud for power grids

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>



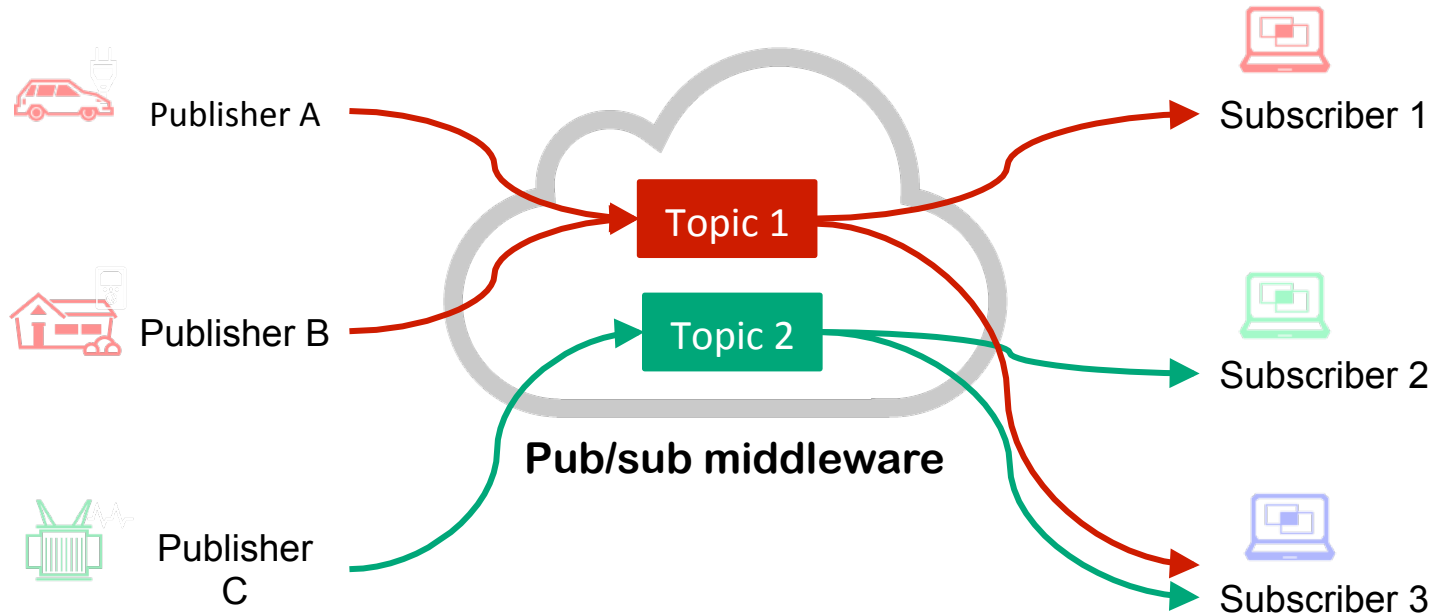
Smart grid communication pattern variation

- **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

Energie Data Services Nederland

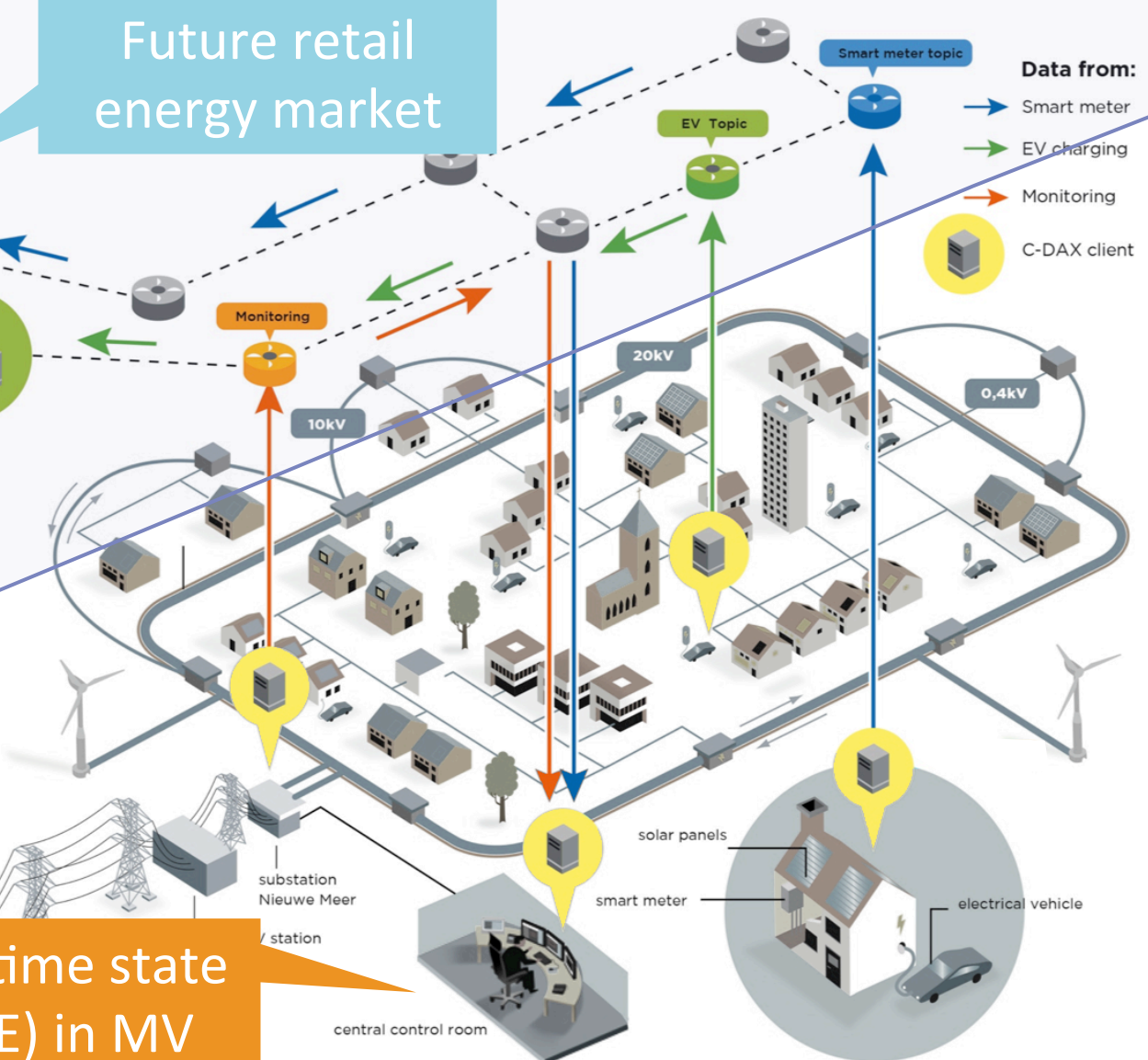
E-Mobility Service Provider

Smart charging

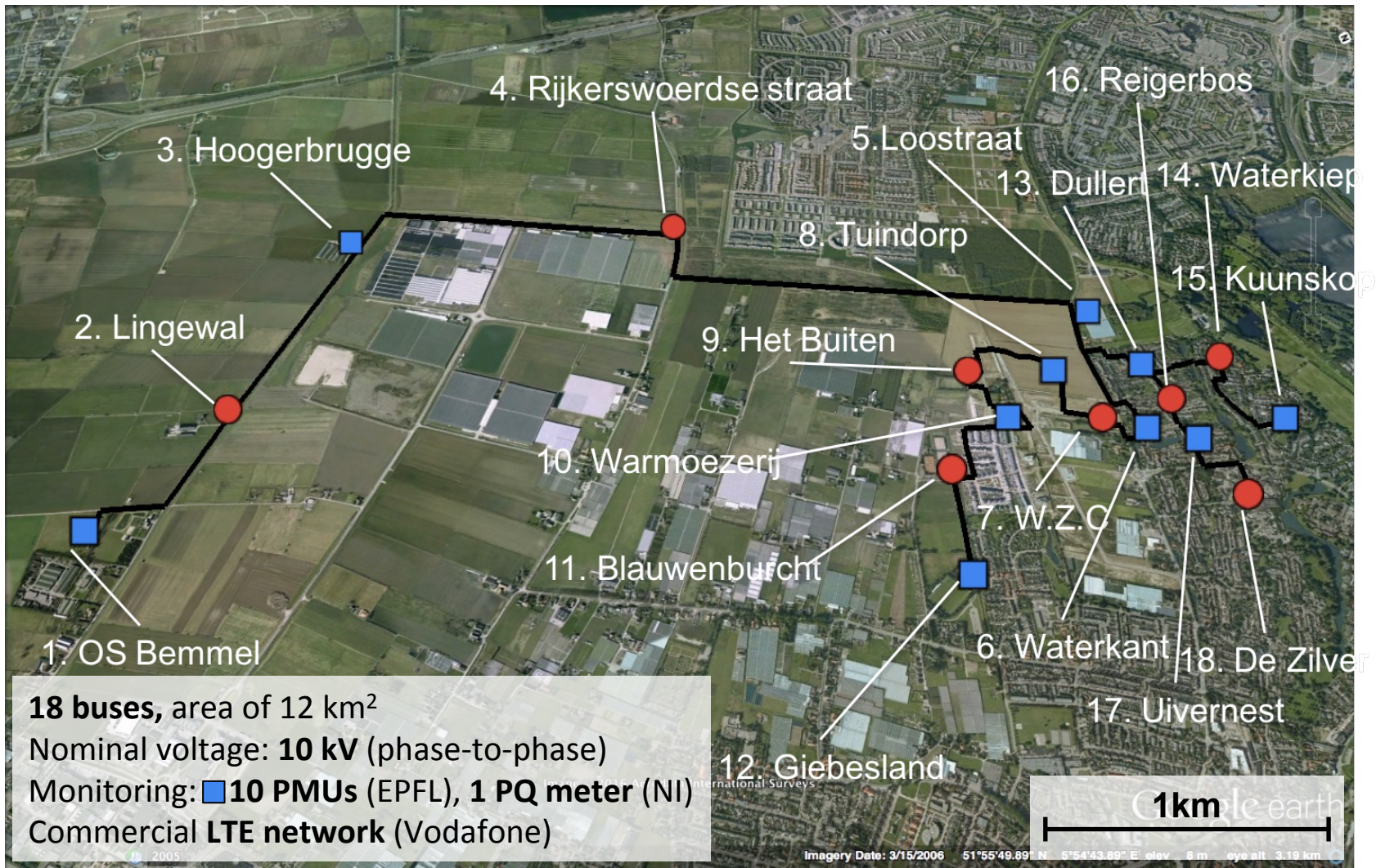
PMU-based real-time state estimation (RTSE) in MV

Data from:

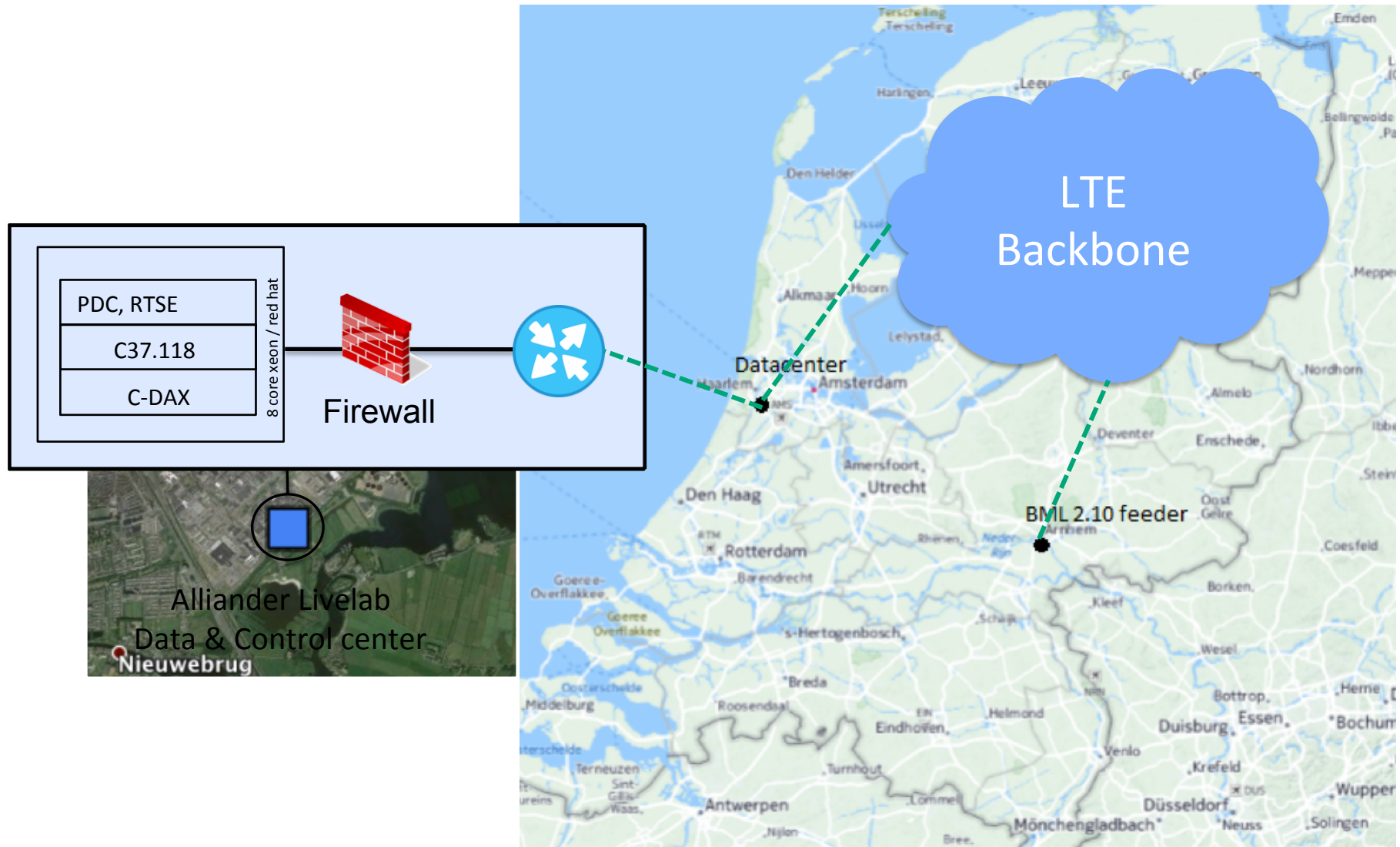
- Smart meter
- EV charging
- Monitoring
- C-DAX client



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



Field trial setup: Alliander data center

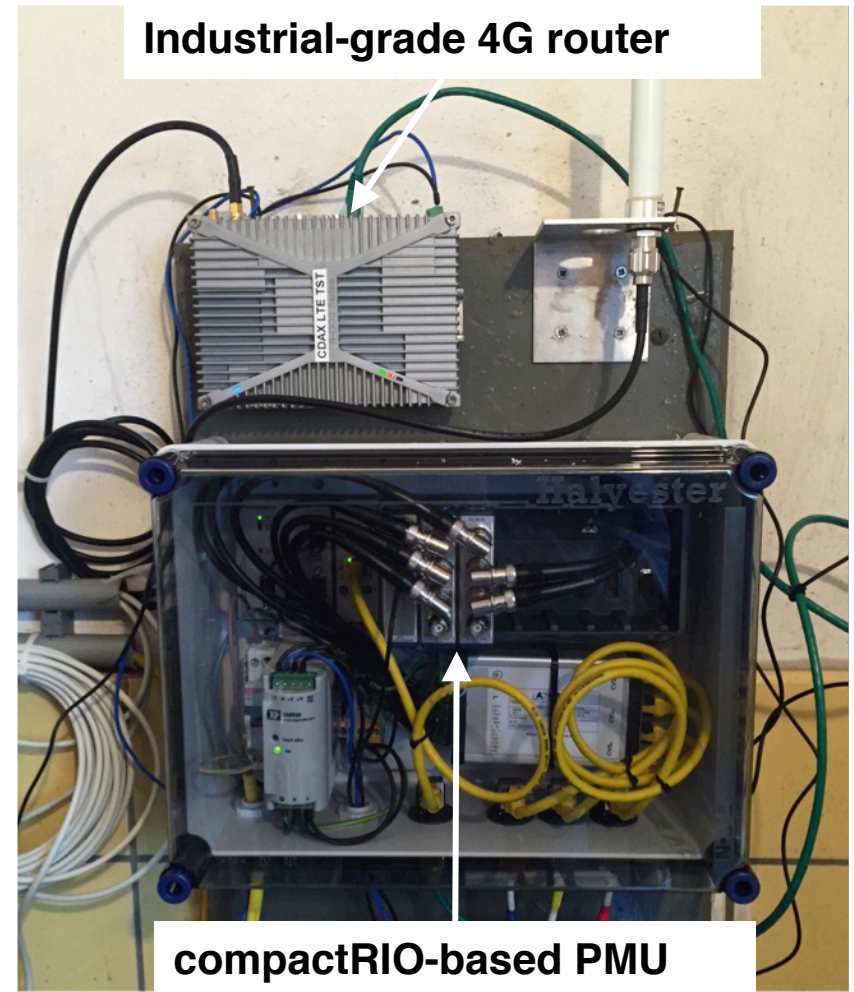


Phasor Measurement Units – The EPFL PMU

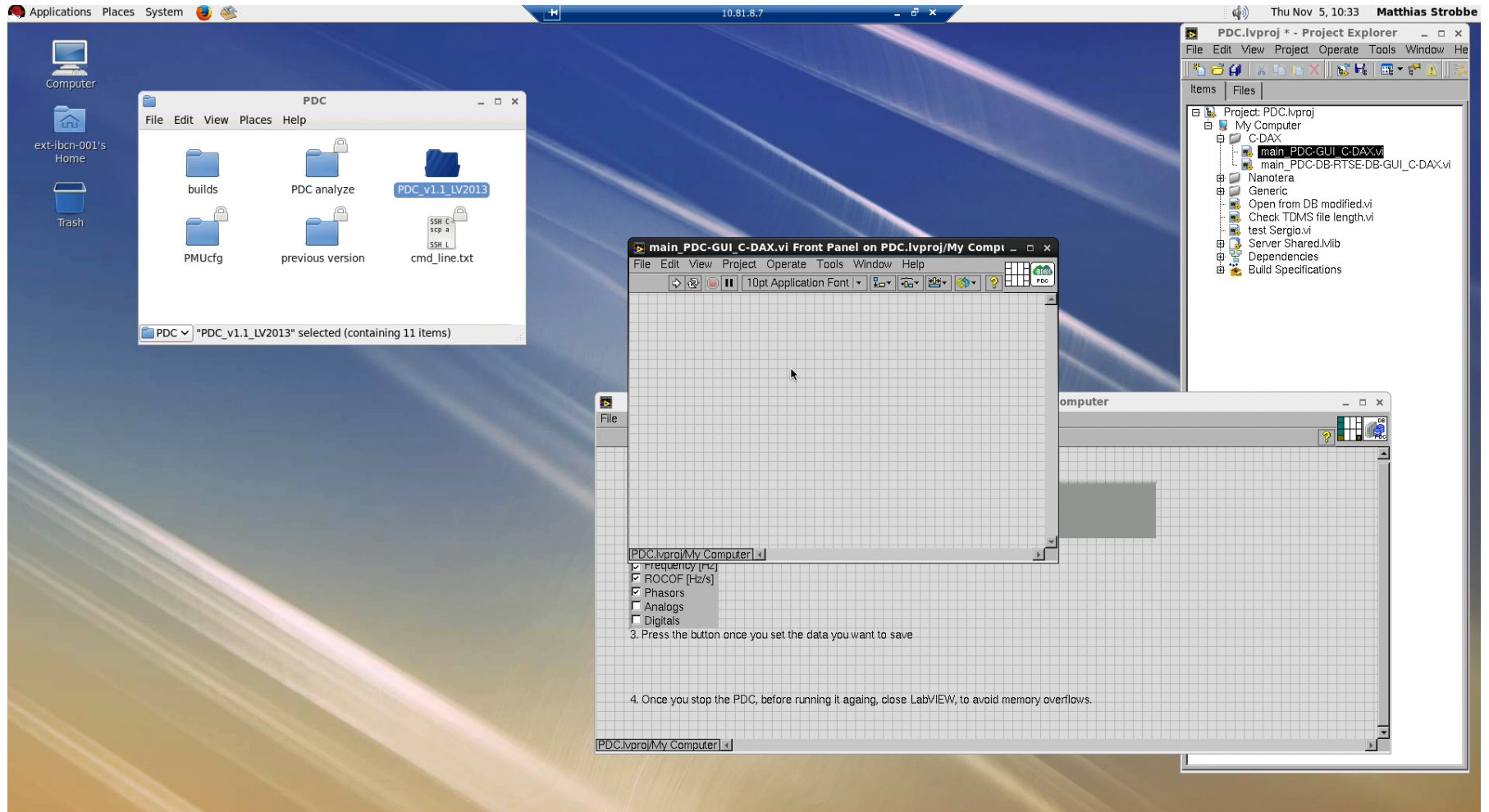
- First PMU worldwide **specifically designed for ADN** operating conditions
- Rugged and compact **NI-compactRIO** enclosure to fit in reduced spaces
- First worldwide **FPGA-based PMU** (high speed and determinism)
- Equipped with a ± 100 ns (max error) stationary **GPS module**
- Metrologically characterized 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**



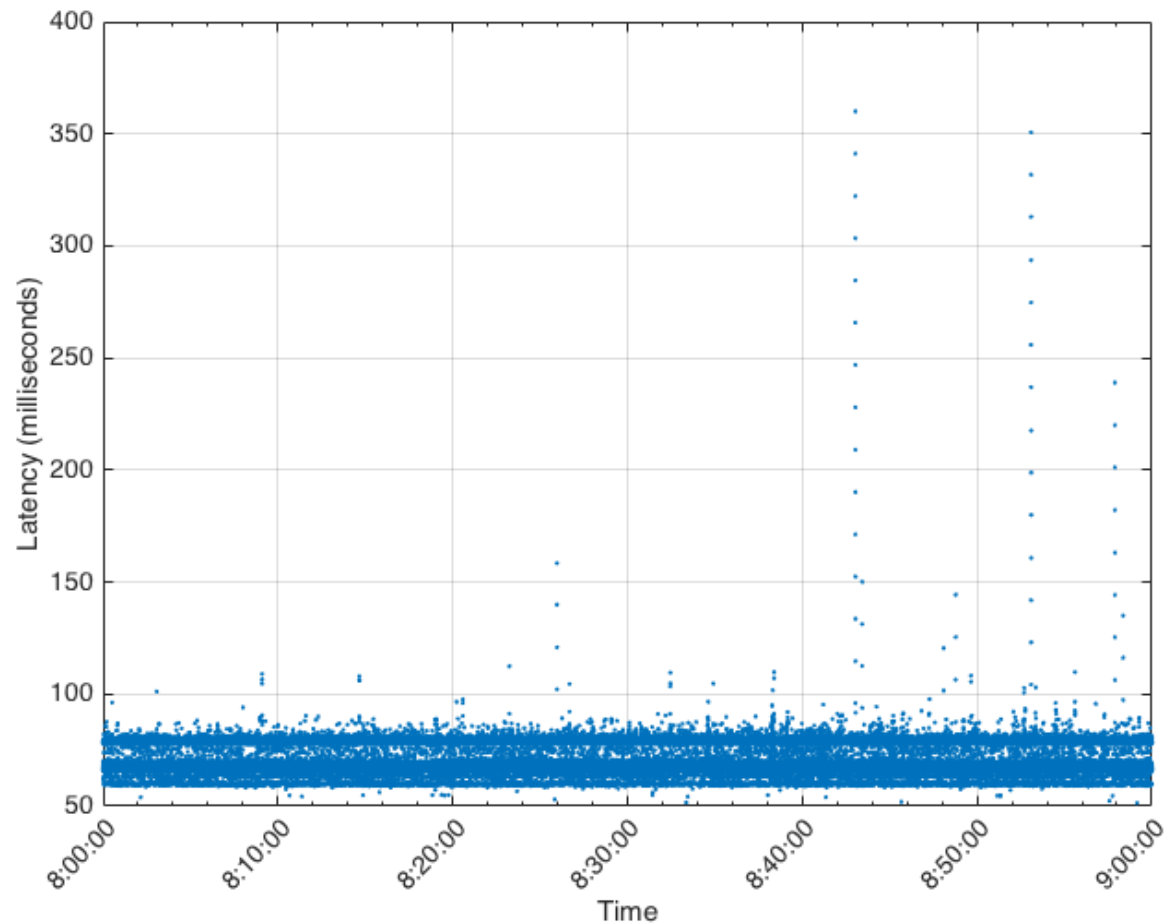
Substation setup



Demo

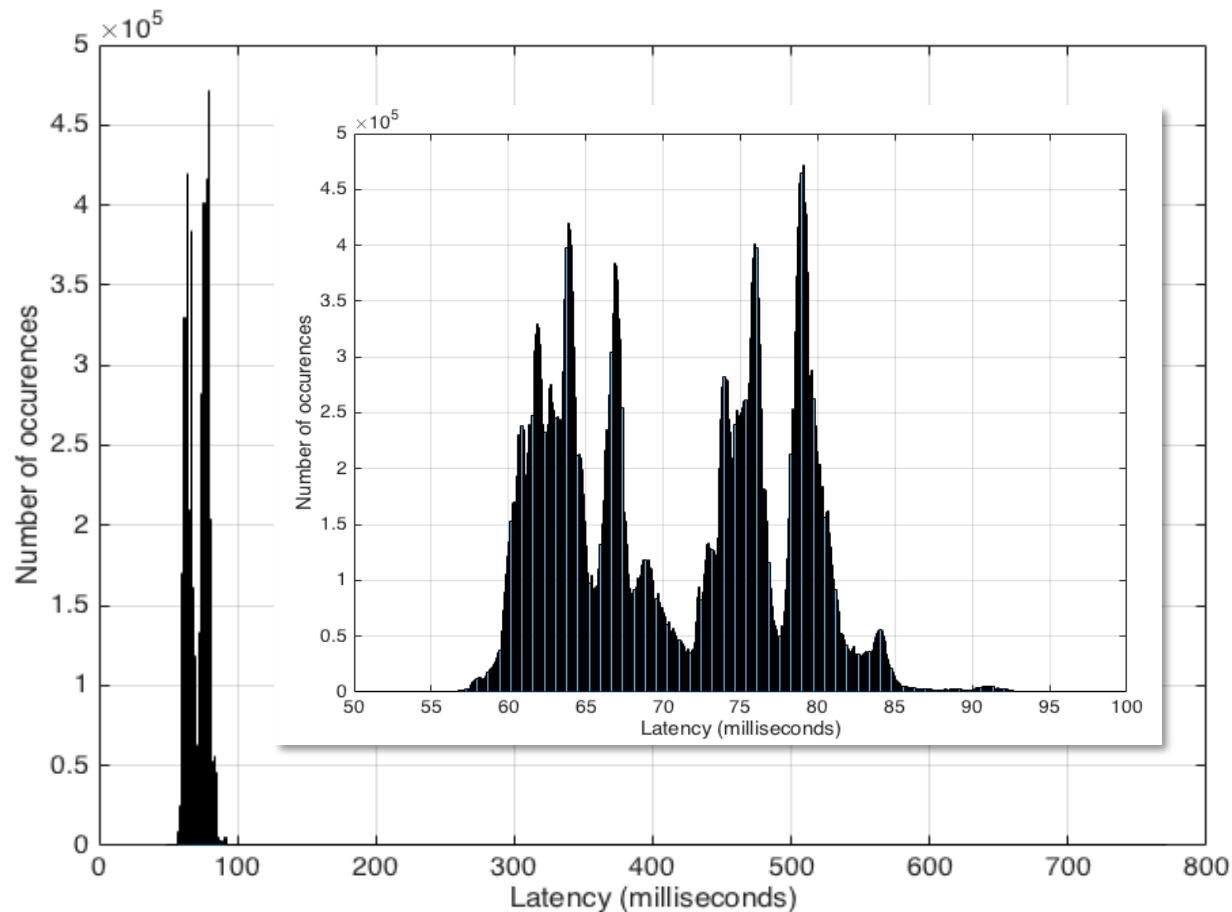


Synchrophasor data latencies (4G network)



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

70.9 ms

Stdev

8.1 ms

Max

770.5 ms

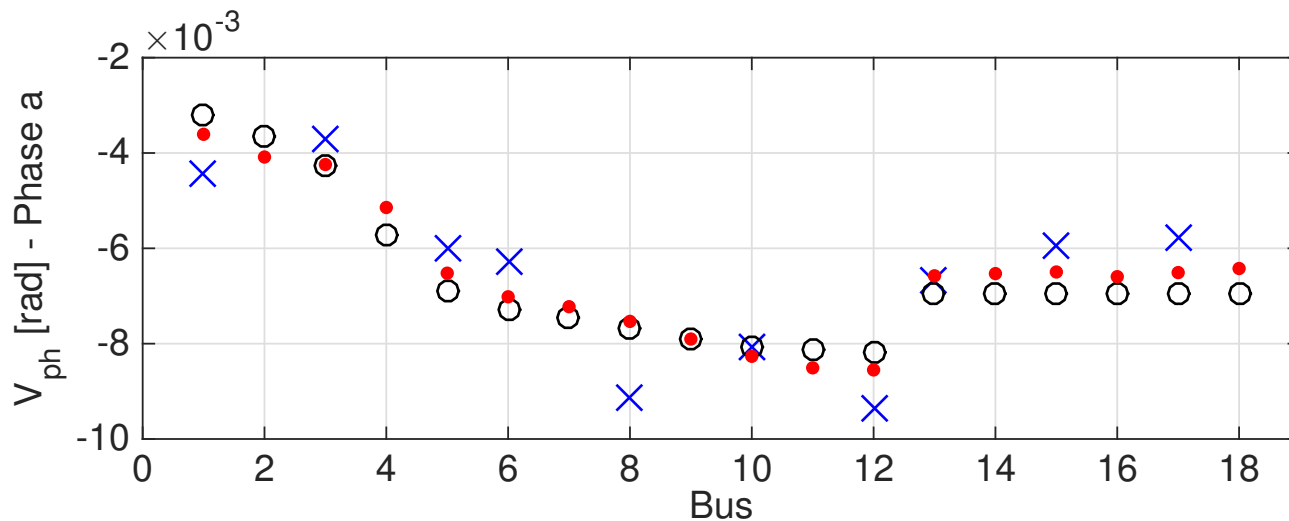
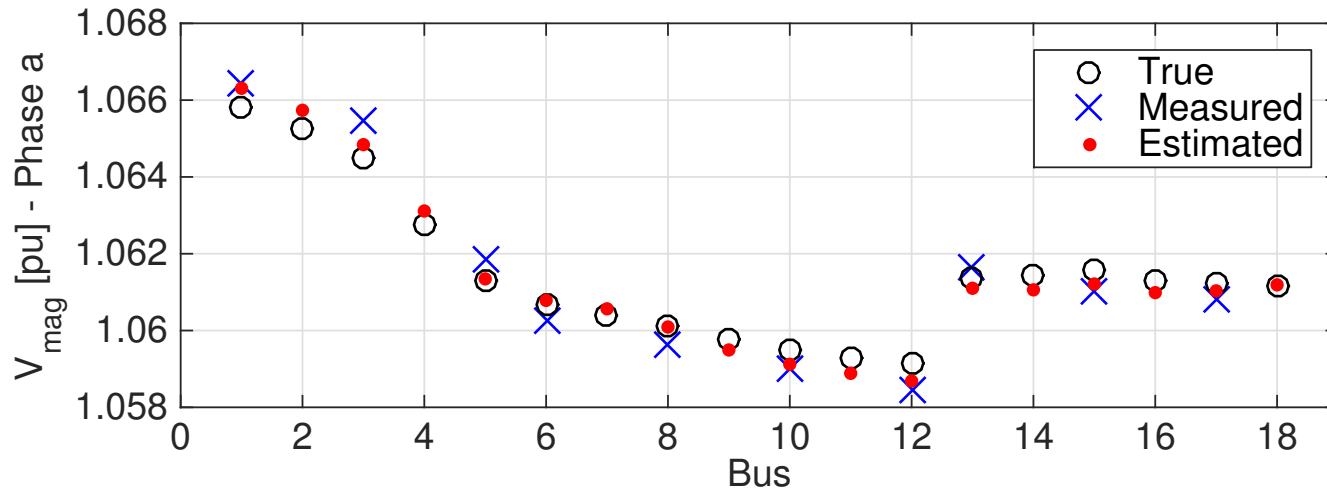
Min

49.2 ms

Data Loss (%)

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
- 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?
 - Evaluation of the **business case** of flexibility?
 - Convincingly demonstrate flexibility exploitation in the real world?

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

Thank you ... any questions?

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