ALGORITHMS AND COMMUNICATIONS FOR SMART GRIDS: KNOWING AND CONTROLLING POWER CONSUMPTION

Nasrin Sadeghianpourhamami, Kevin Mets, Leen De Baets, Matthias Strobbe and Chris Develder

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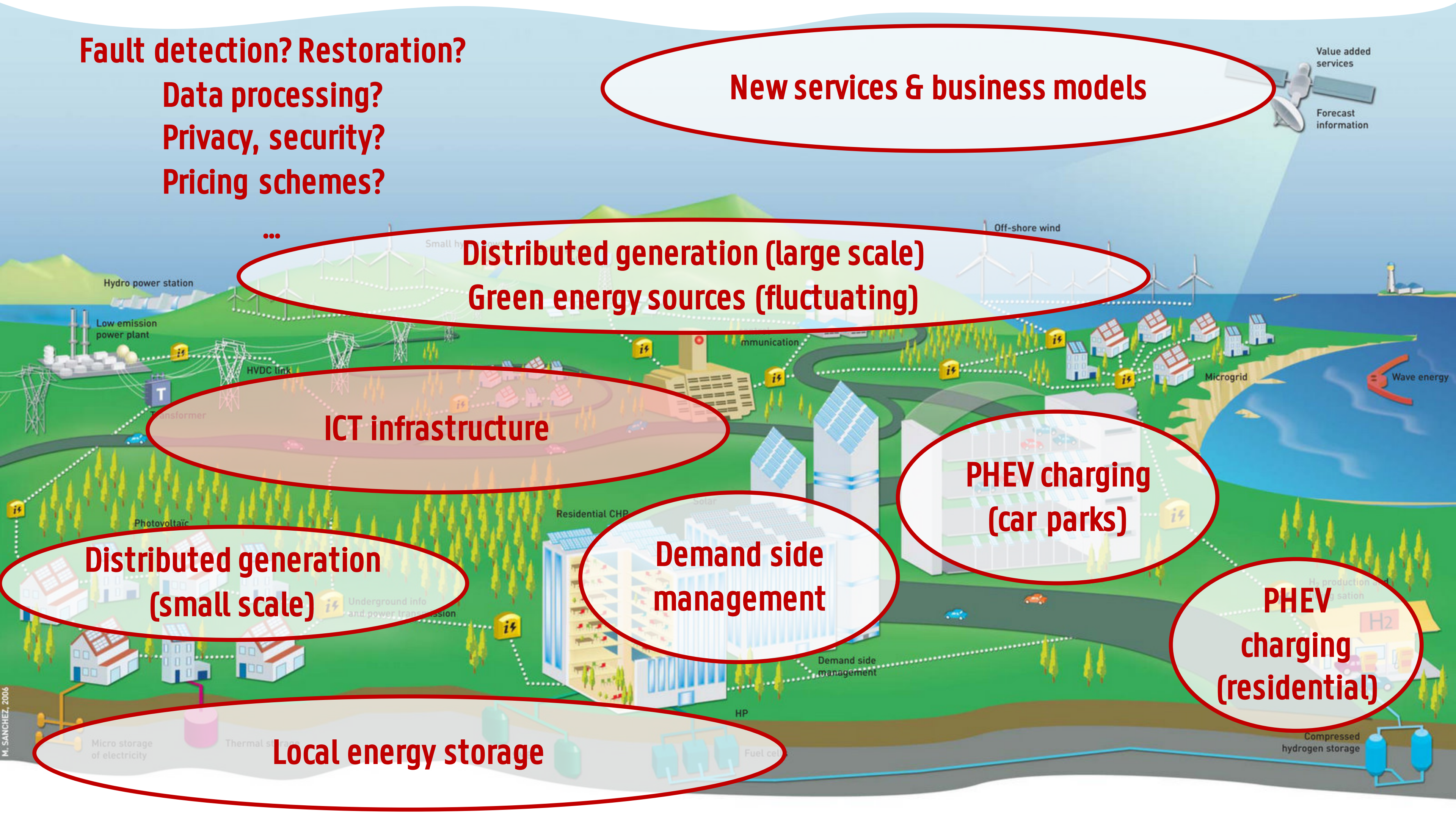
SMART GRIDS



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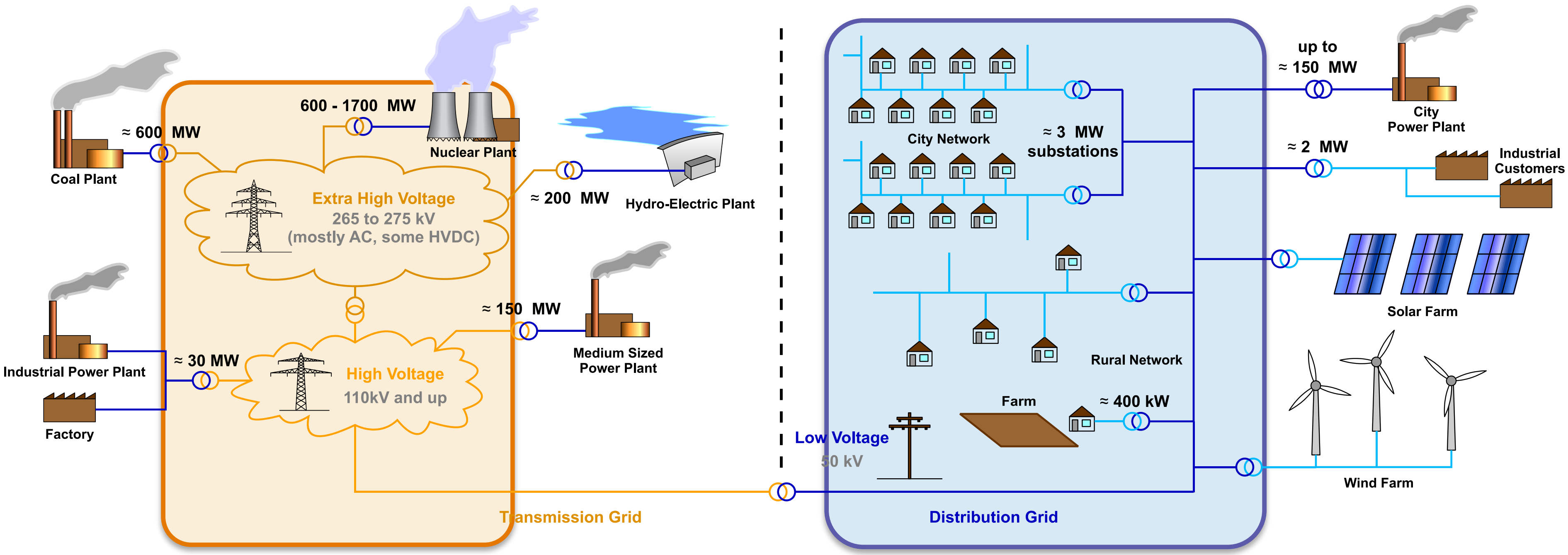
POWER GRID STRUCTURE

Transmission network (operated by TSO)

Distribution network (operated by DSO)



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OUTLINE

Part I: Algorithms for DSM/DR

- Example 1: Peak shaving
- Example 2: Wind balancing

Part II: Data analytics

- Clustering smart metering data
- EV usage analysis
- Flexible usage of white good appliances

Part III: Non-intrusive load monitoring

- Appliance classification w/ convolutional nets
- Appliance classification w/ elliptical Fourier descriptors

OUTLINE

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

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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>?

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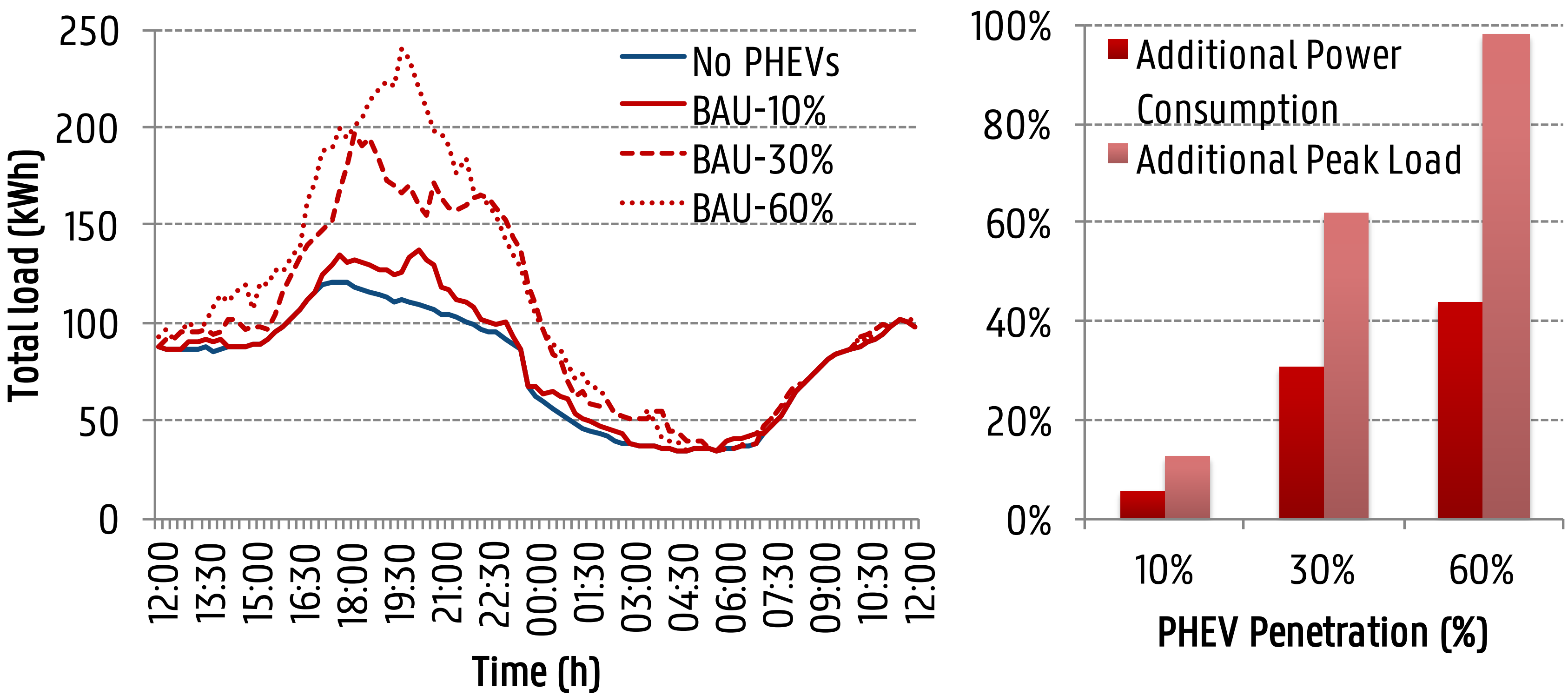
Impact of EV charging

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



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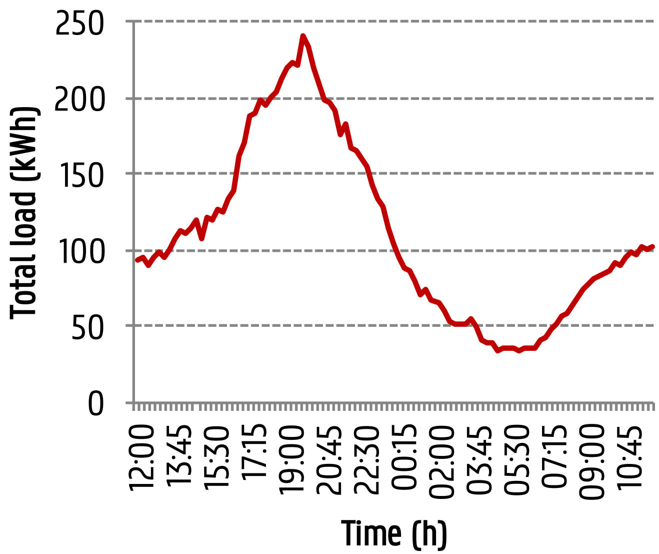
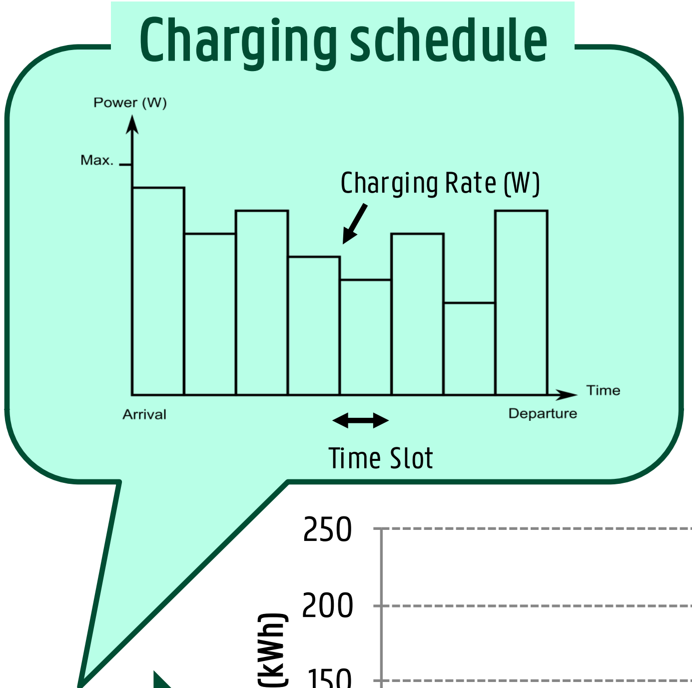
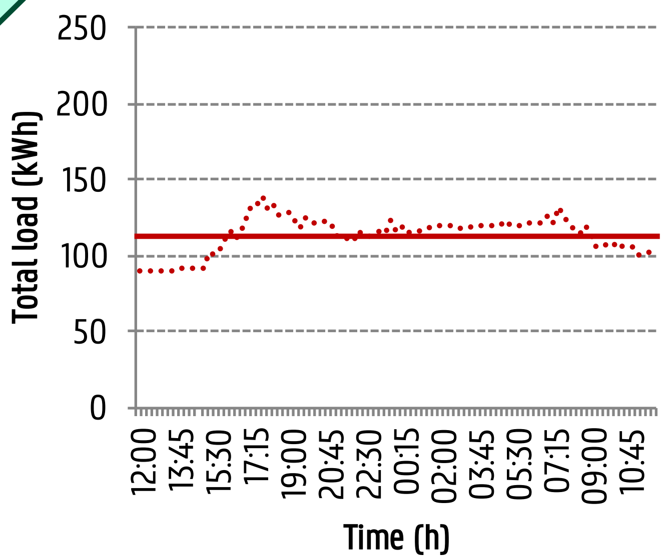
Controlling EV charging?

Objectives:

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







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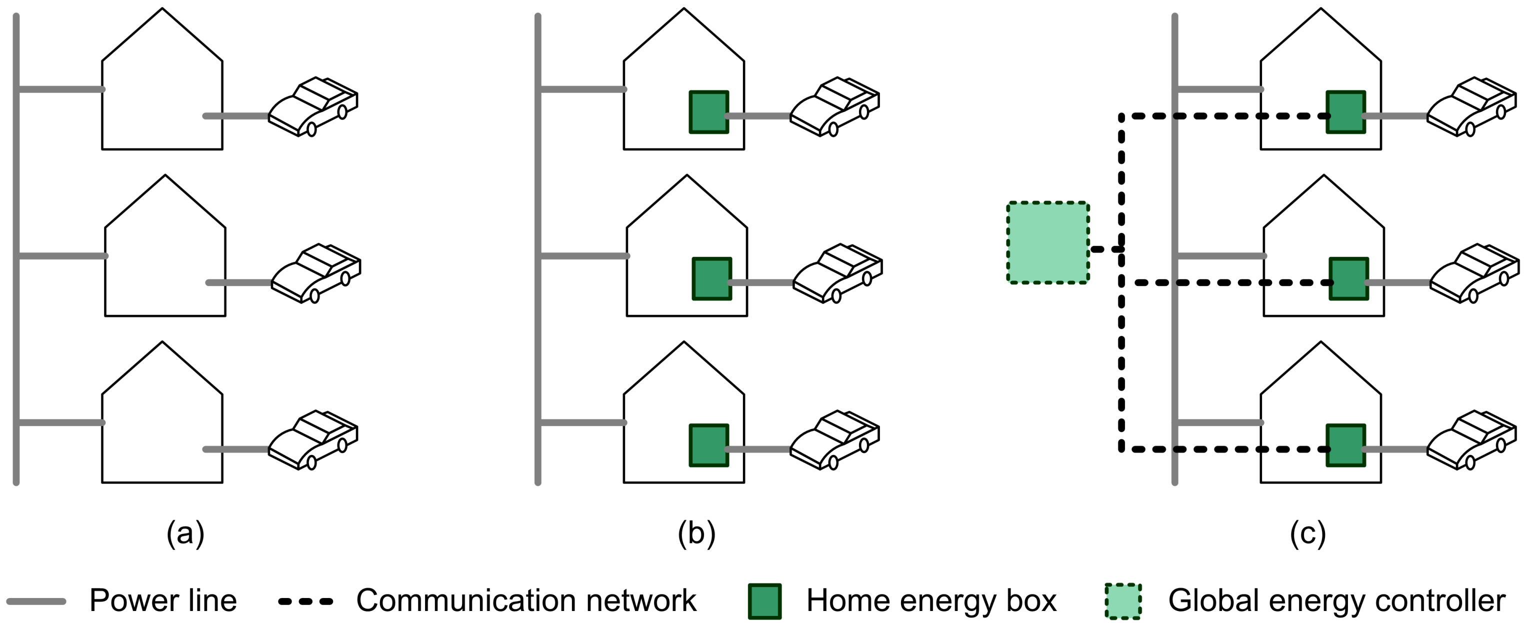
Smart charging: QP

BAU (uncontrolled) | **Local control (QP)** | **Global control (QP), Market MAS**



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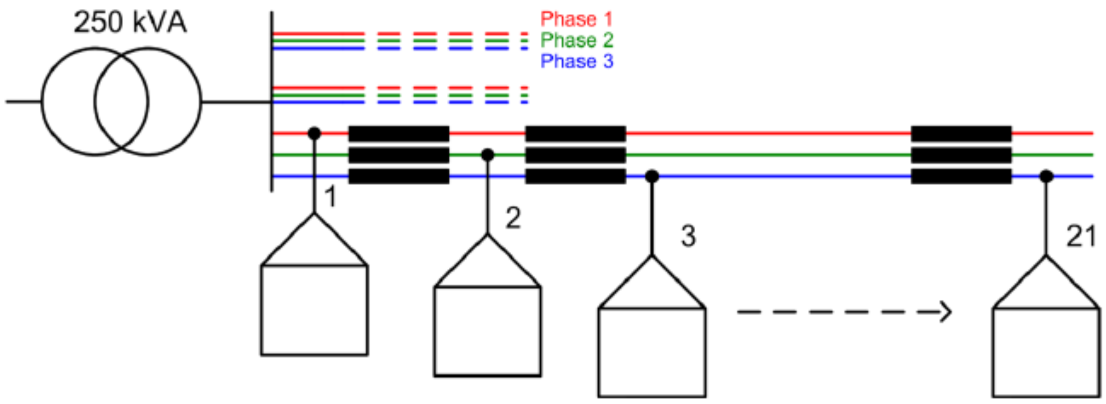
Case study

- 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

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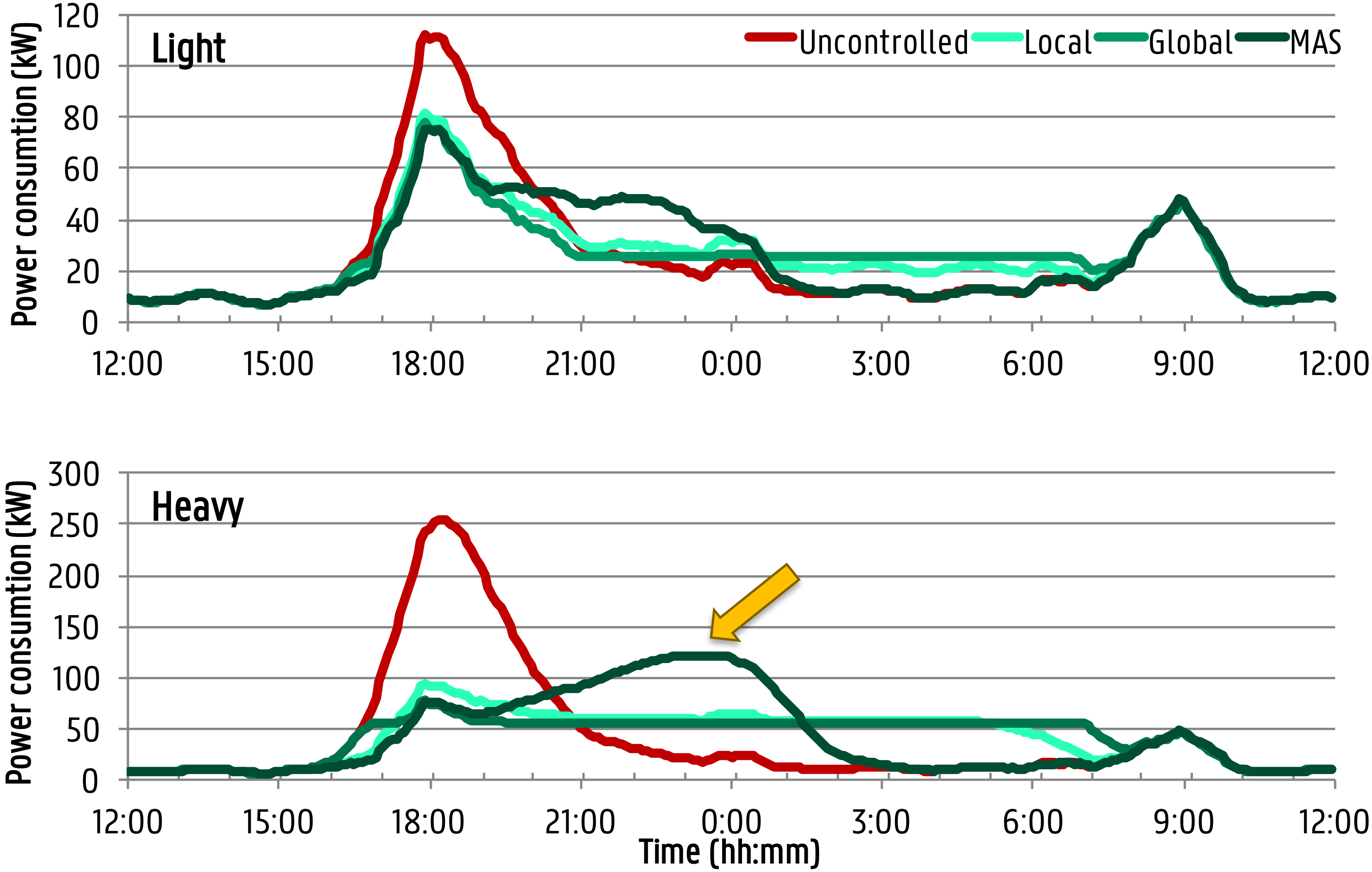
Results (1) – Load profiles



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OUTLINE

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

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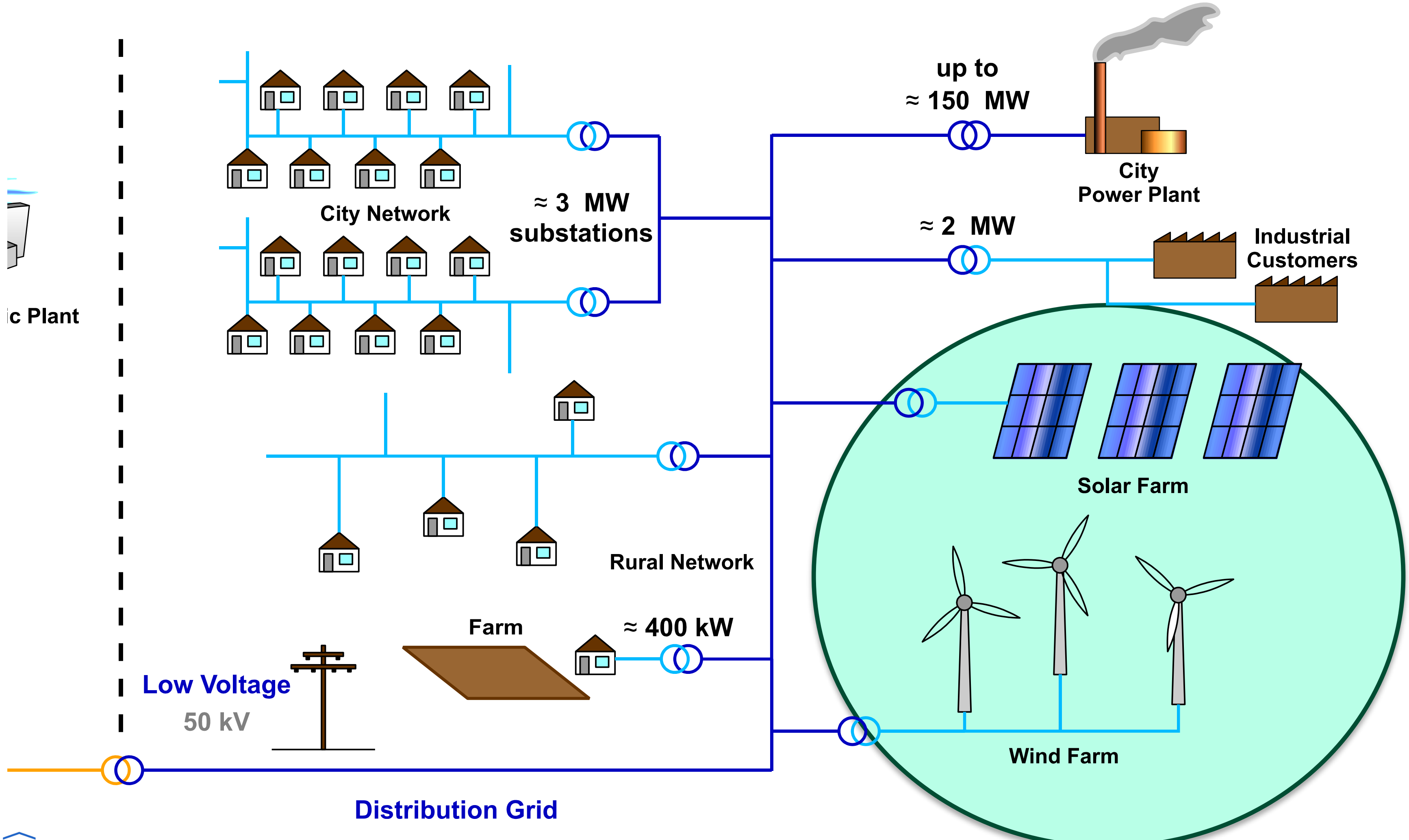
Distributed generation (DG)



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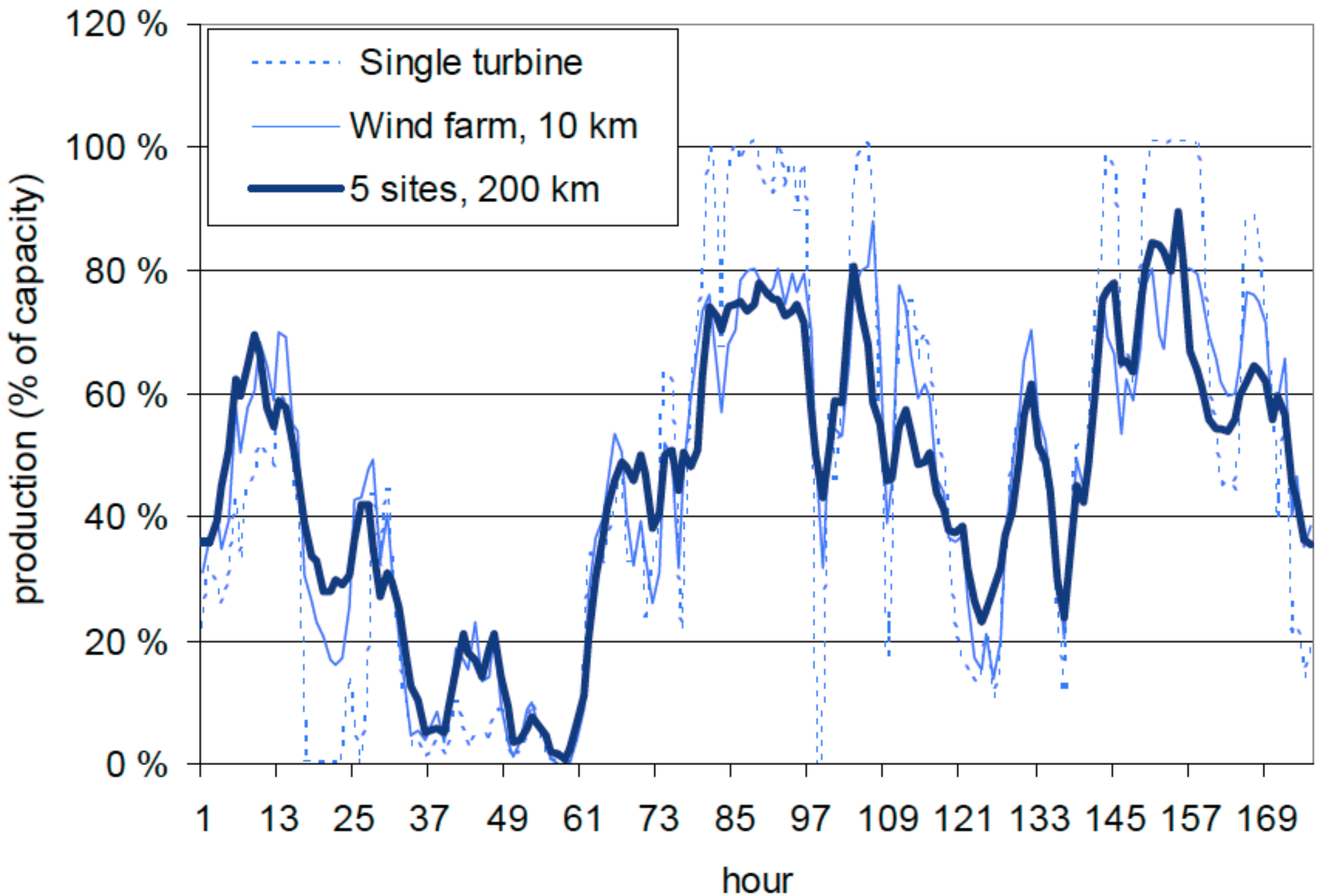
A typical wind profile



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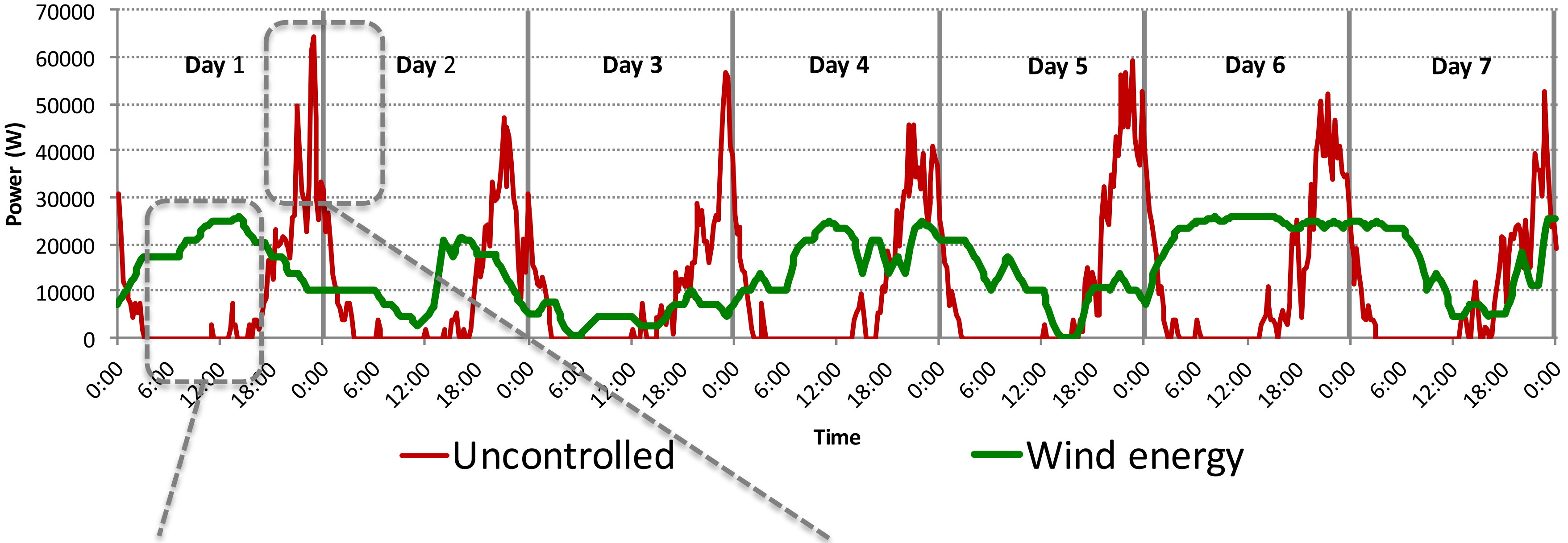
Wind balancing with EV charging



Supply/demand imbalance & **High peak loads**

- Inefficient use of RES
- Imbalance costs

} Undesirable!

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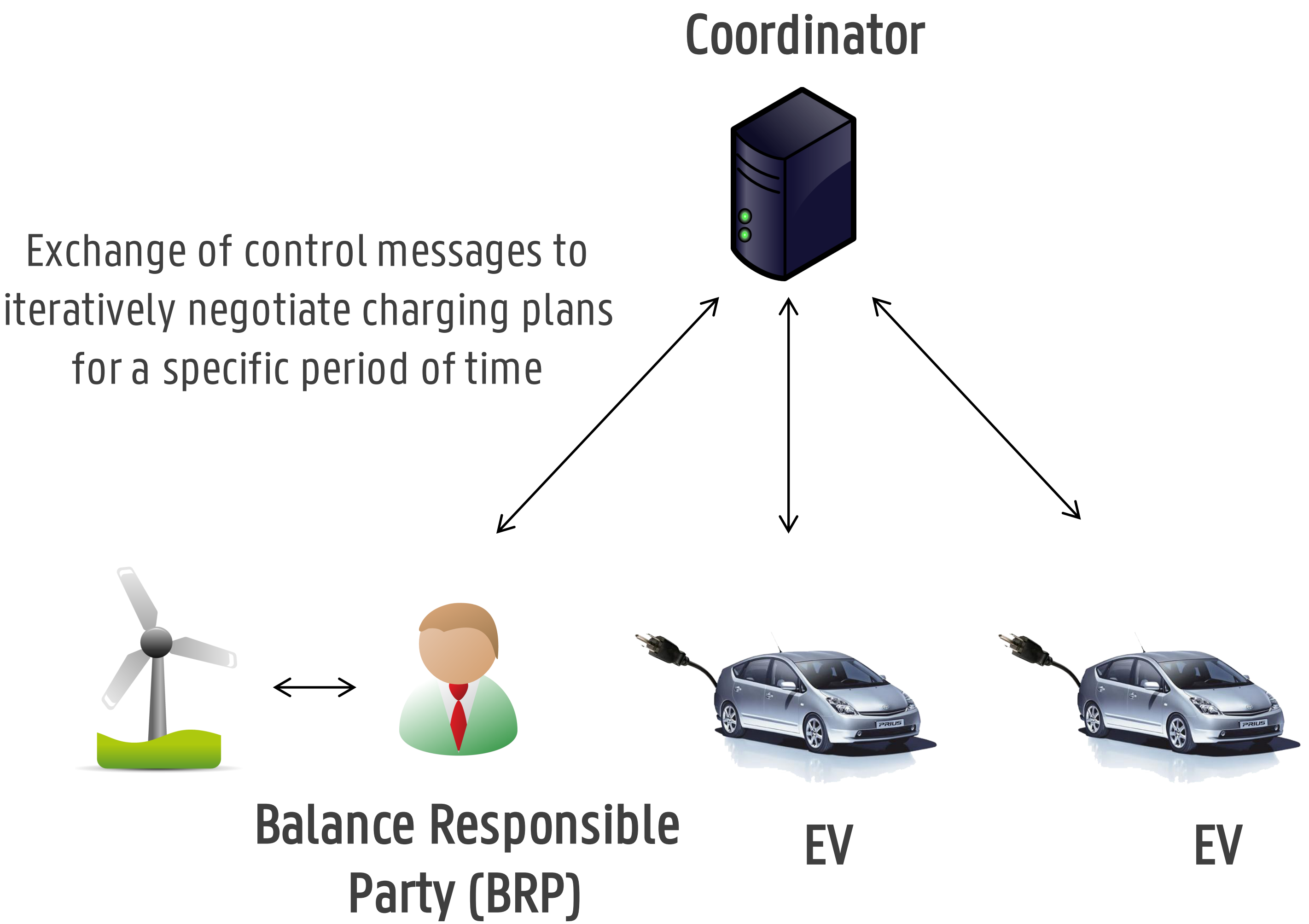
Distributed control



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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

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

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

1 BRP problem

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

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

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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:

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

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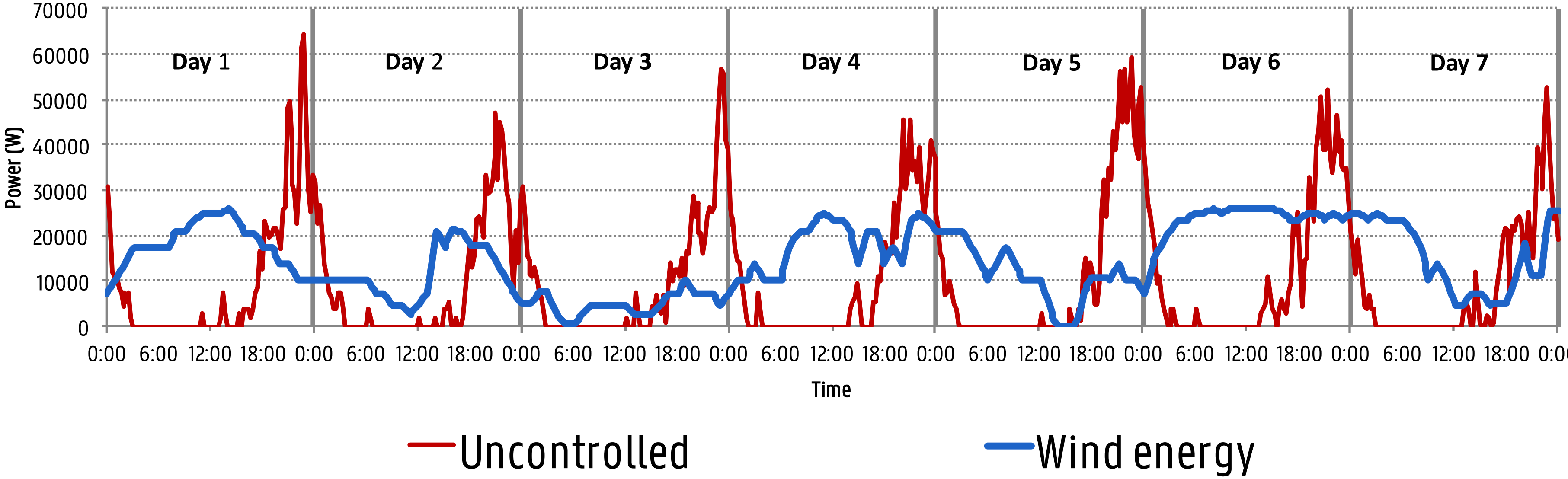
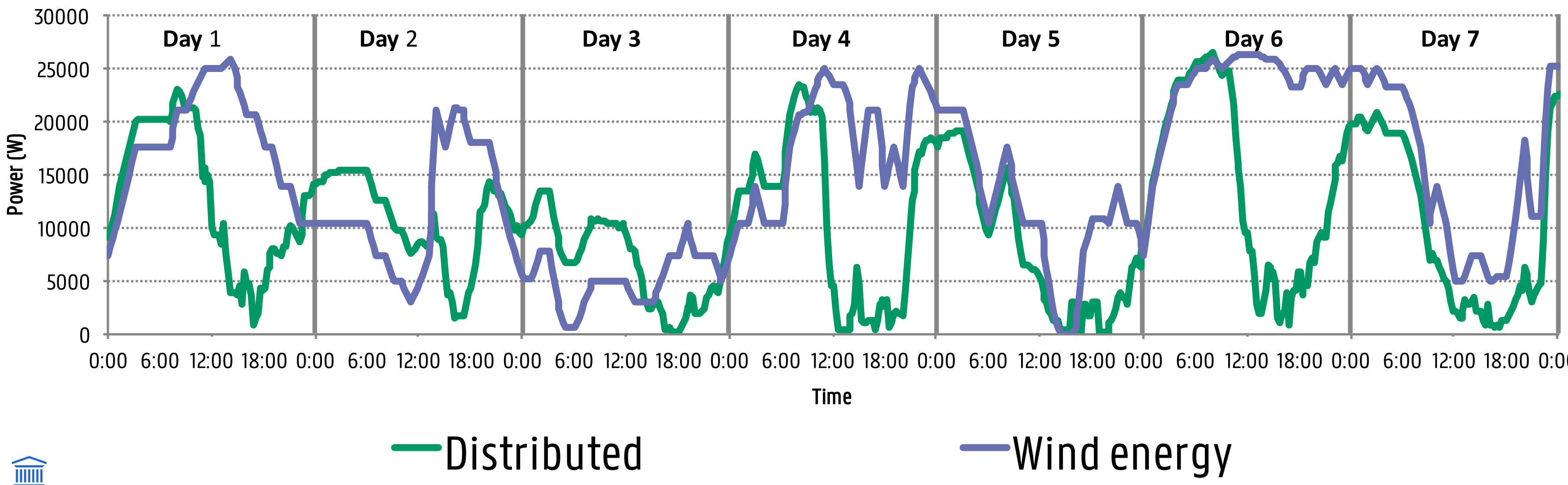
Results: Uncontrolled BAU vs. Distributed





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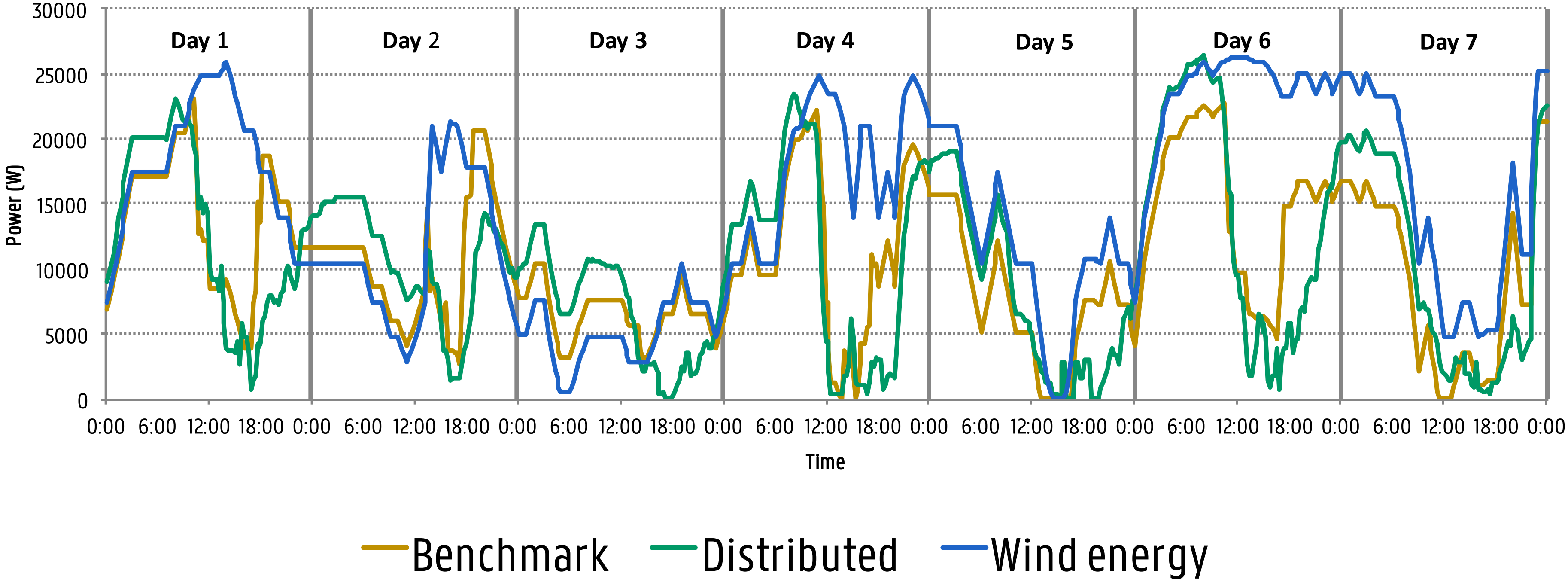
Results: Distributed vs. Benchmark



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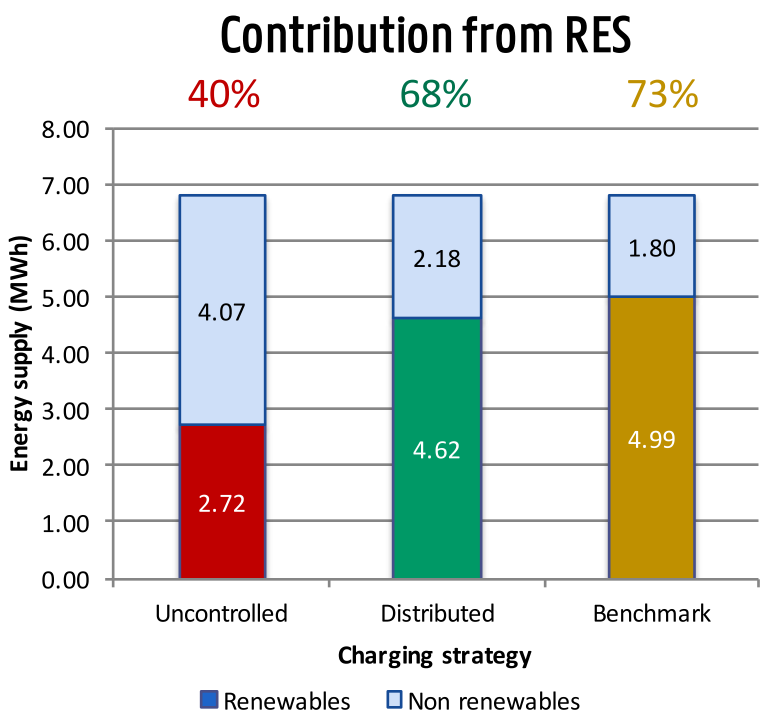
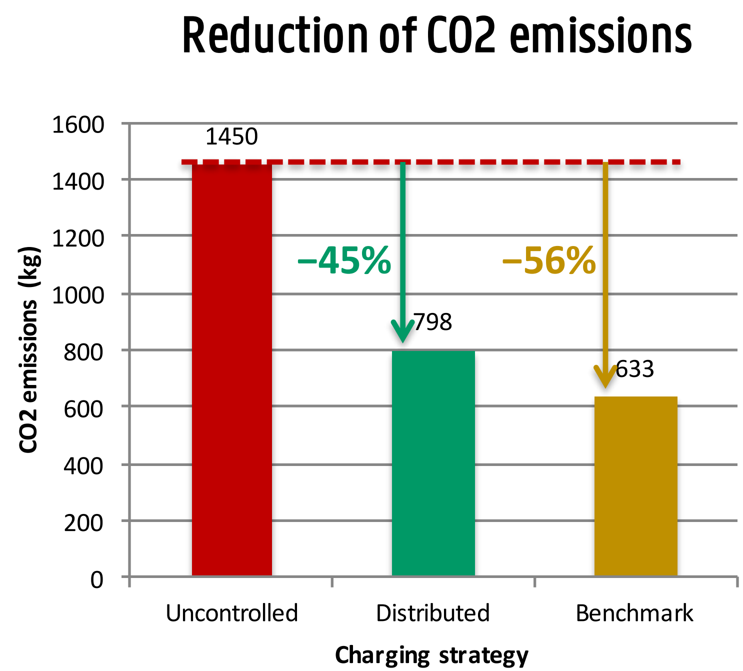
Results: Energy Mix





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

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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, Vol. 7, No. 5, Jul. 2015, pp. 2250-2259.

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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
  - …

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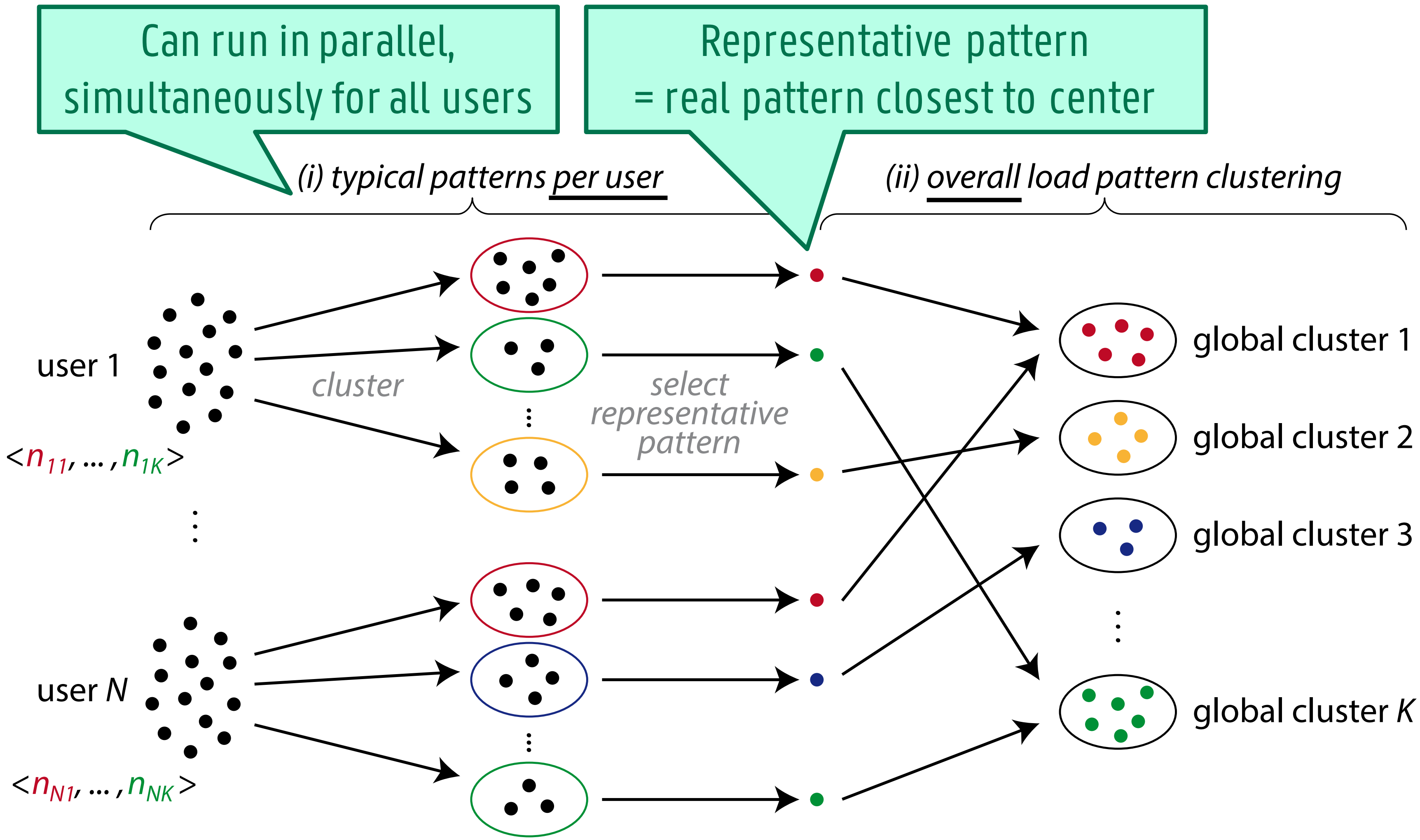
Two-stage load pattern clustering



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Core ideas

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

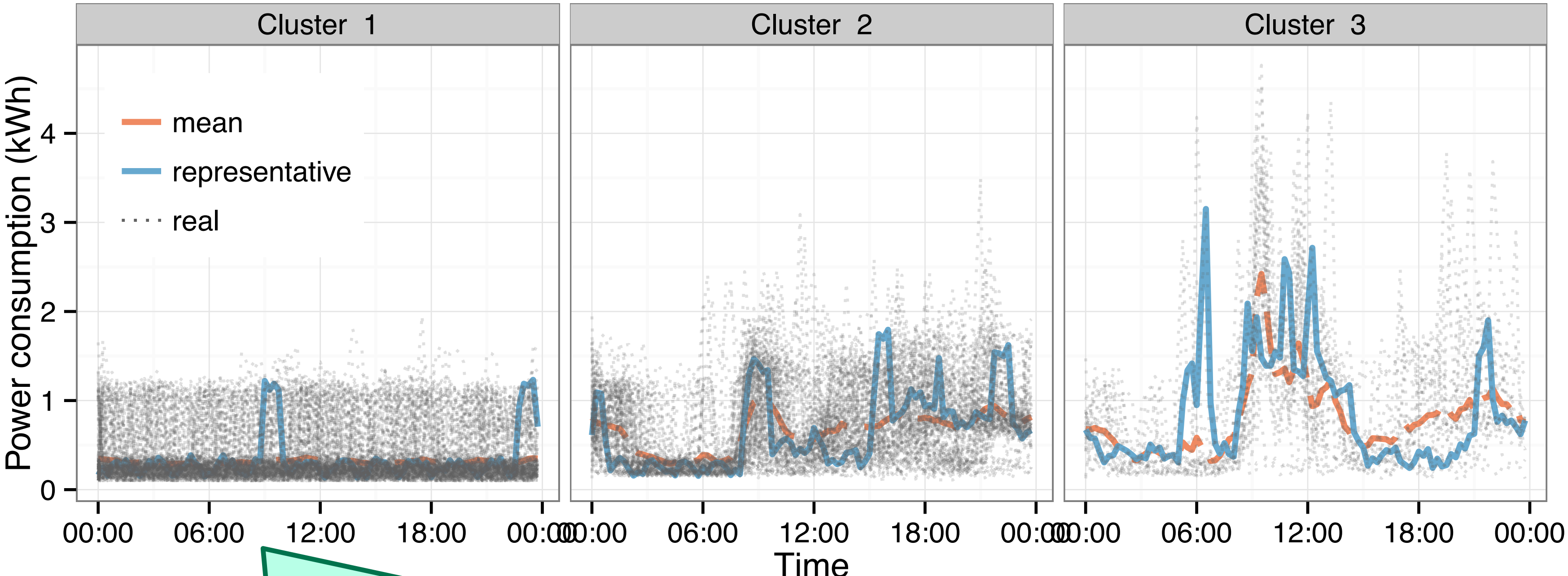
- G-means (instead of k-means) [Hamerly2003]

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!

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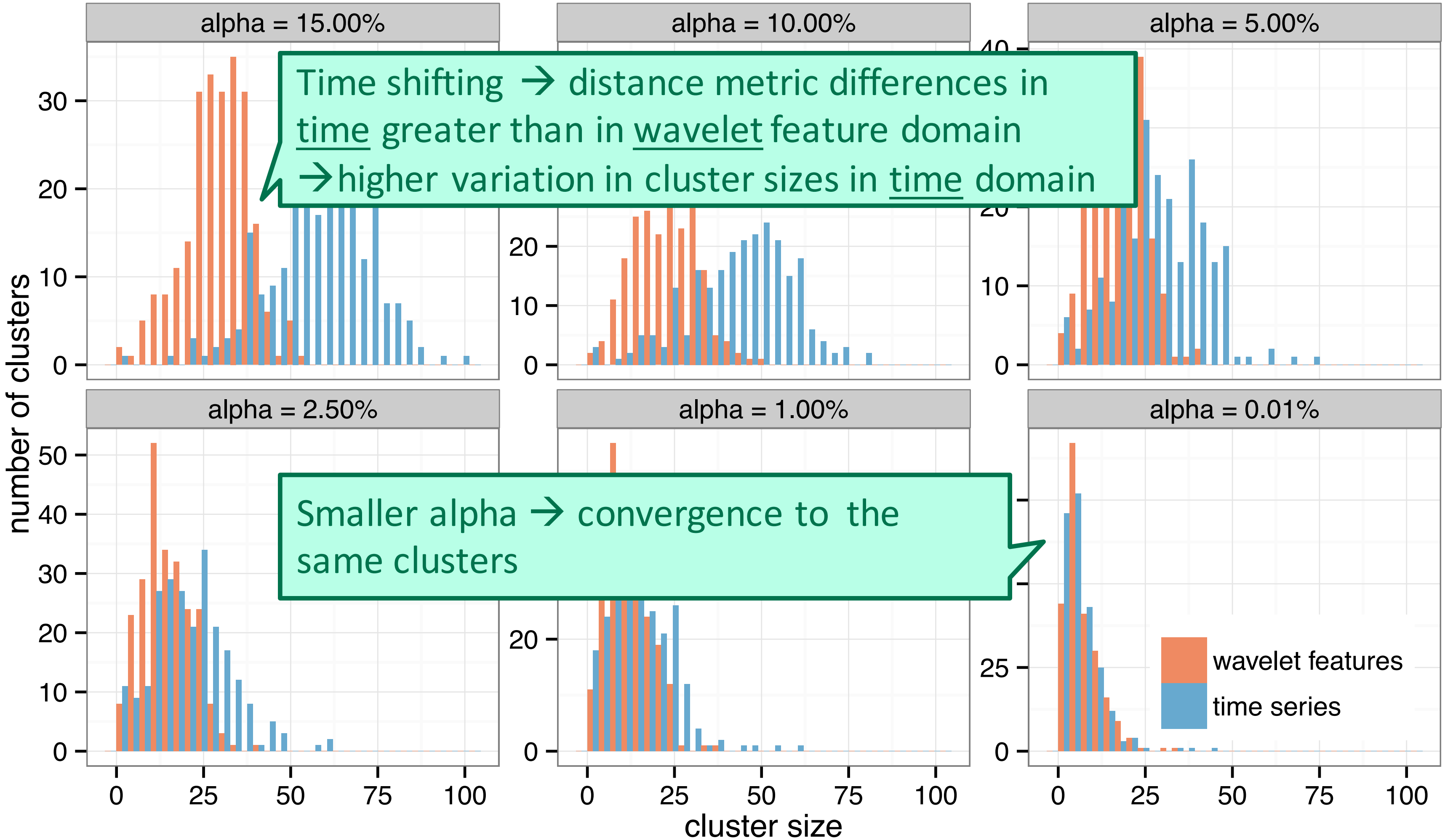
Time vs wavelet domain: Number of clusters



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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

N. Sadeghianpourhamami, N. Refa, M. Strobbe and C. Develder, **"Quantitive analysis of electric vehicle flexibility: A data-driven approach"**, Int. J. Electr. Power Energy Syst., Vol. 95, Feb. 2018, pp. 451-462.

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MODELING EV CHARGING

Literature:

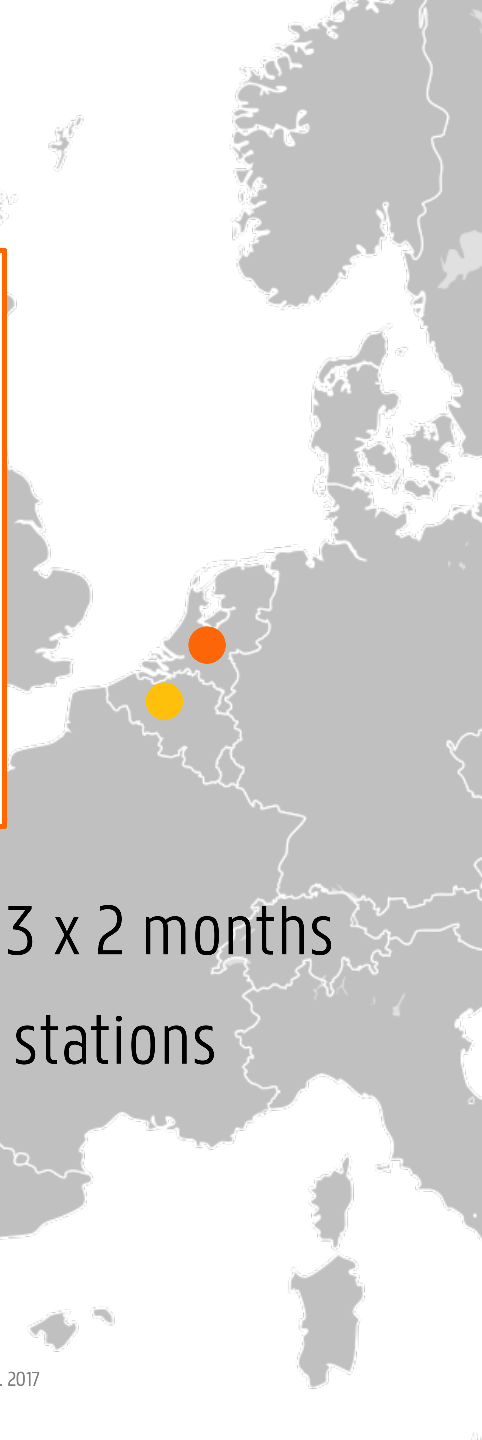
- Model EV usage from regular vehicle usage
- Aggregated EV load estimation
- Pre-defined EV user types (e.g., residents, taxis, commuters…)
- Flexibility as fraction of time spent charging
- …

Gap: data-driven EV modeling & real-world flexibility assessment

1. Typical behaviors in terms of time of arrival and departure?
2. Statistical models of sojourn vs time spent charging?
3. What amount of power can we shift over how much time?

DATASETS: IMOVE (BE) AND ELAADNL

	IMOVE	ELAADNL
PERIOD	03/2012 – 03/2013	01/2012 – 03/2013
# SESSIONS	8 520	1 141 849*
# USERS	134	about 53 000
CAR TYPE	Full EV	Unknown mix
CHARGE POINT	At home	Public
TRIP DETAILS	Yes	No

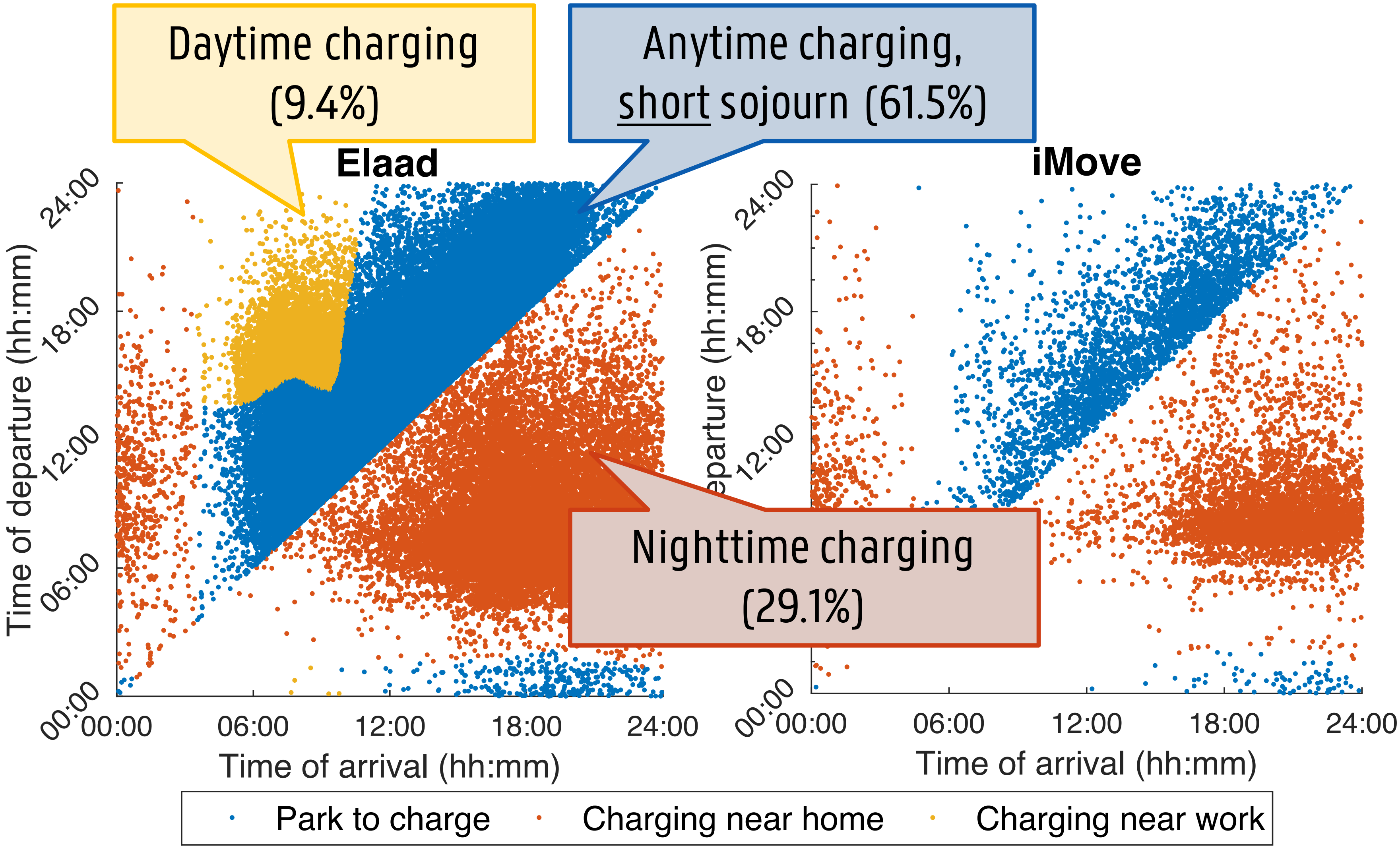


<u>iMove</u>: Flemish EV field trial; data from 50 EVs shared 3 x 2 months

<u>ElaadNL</u>: EV innovation in NL; data from ~3000 public stations

* : Analysis on data from 1 Jan.–31 Mar. 2015 (N = 90 562)

TYPICAL ARRIVAL AND DEPARTURE TIMES (1/2)



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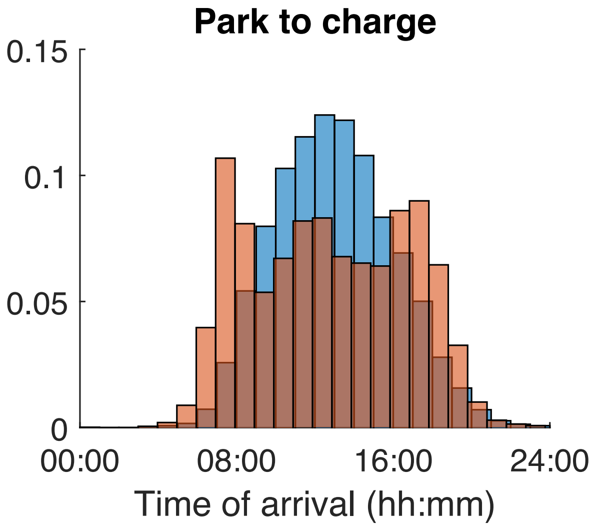
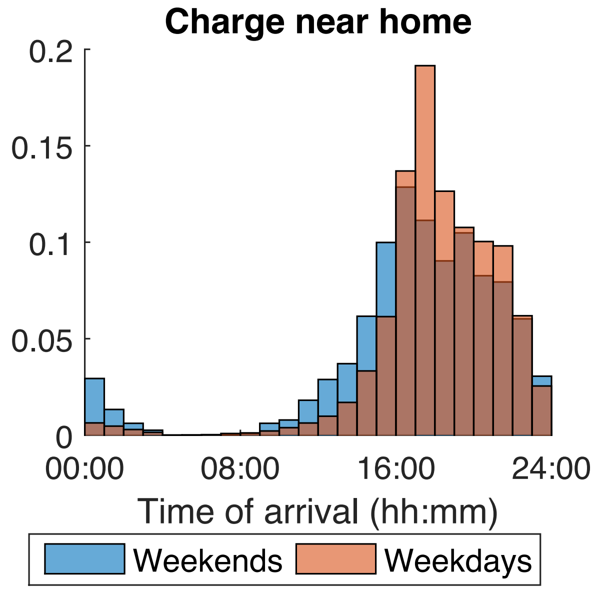
TYPICAL ARRIVAL AND DEPARTURE TIMES (2/2)

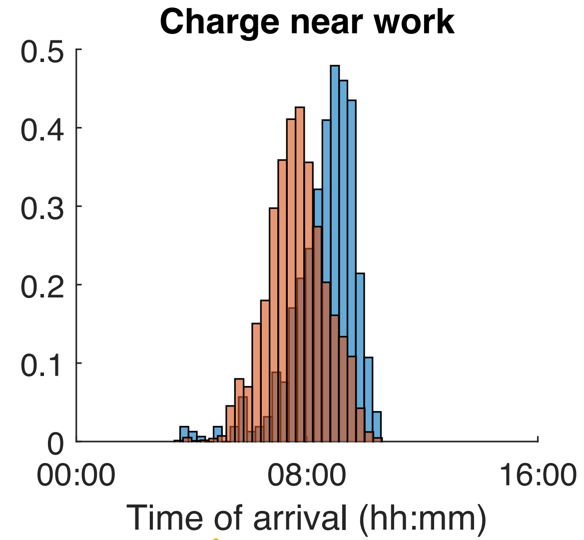
Anytime charging, short sojourn (61.5%)

Nighttime charging (29.1%)

Daytime charging (9.4%)







AM/Noon/PM peaks on weekdays

Shift to later times on weekends

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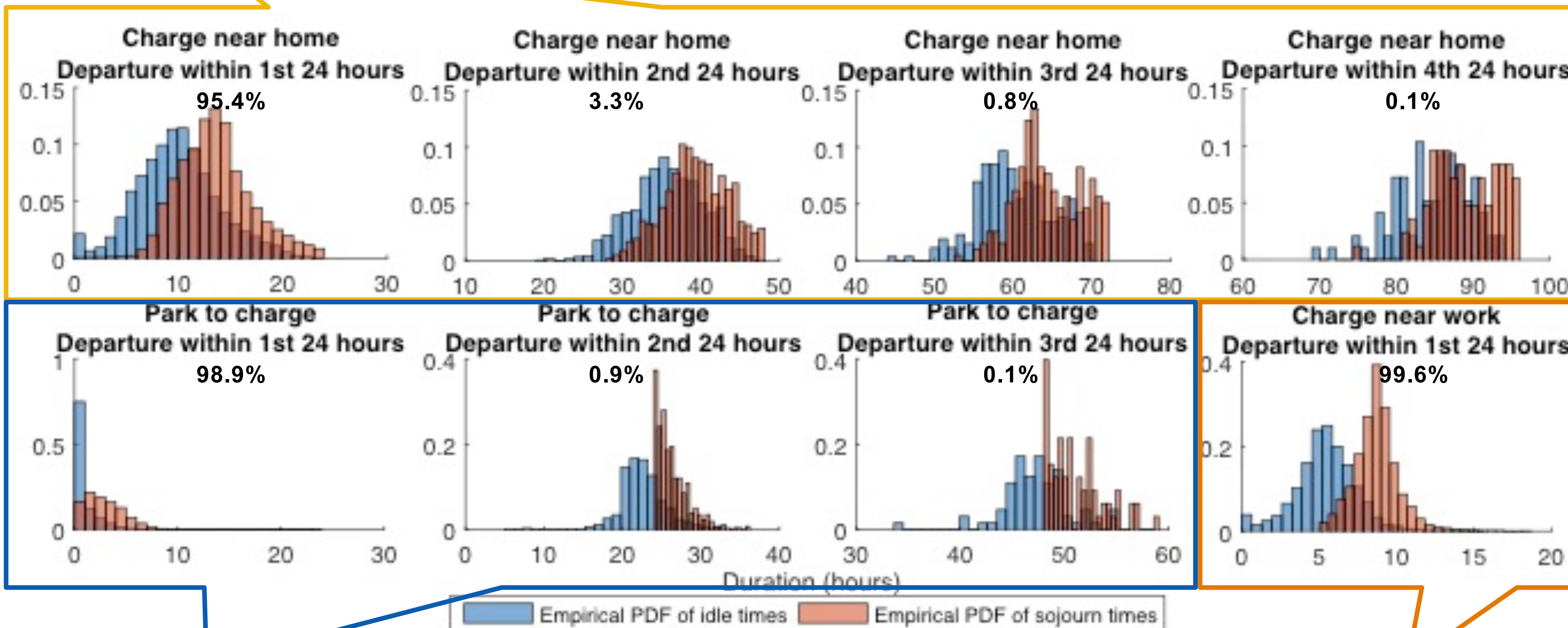
SOJOURN AND IDLE TIMES (1/2)

Average charging time ≈ 3h 42min



Average idle time ≈ 23min

Average charging time ≈ 3h 44min

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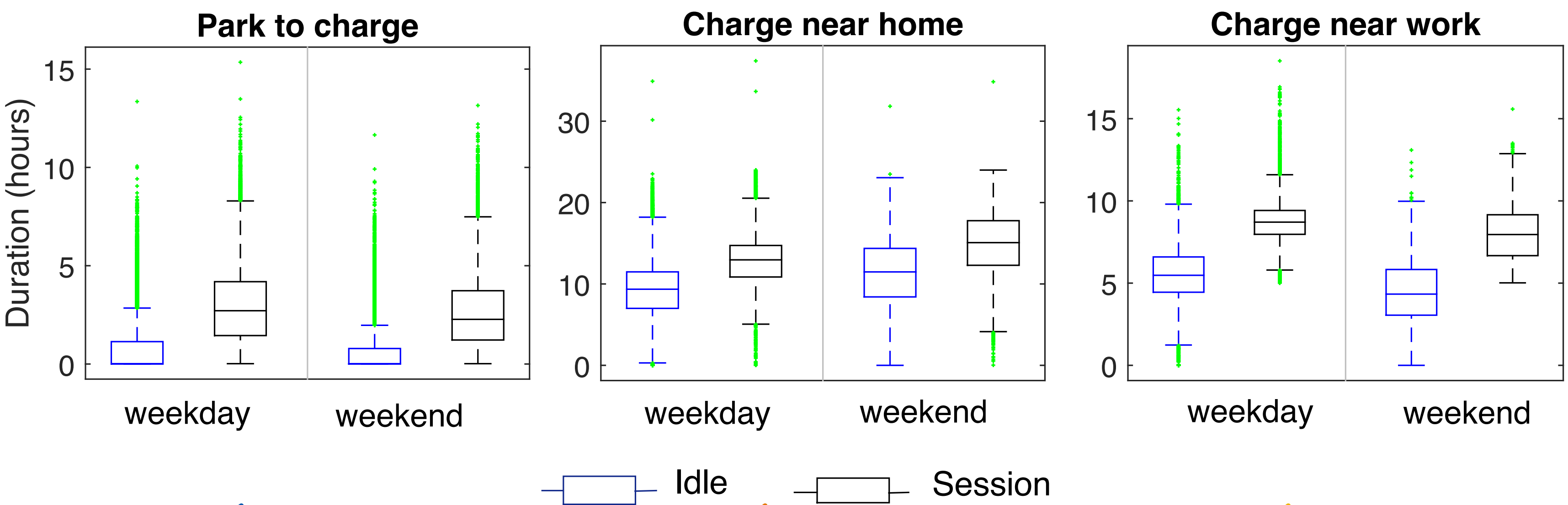

Week ≈ Weekend

Longer in weekend

Shorter in weekend
Lower var. in week

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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]

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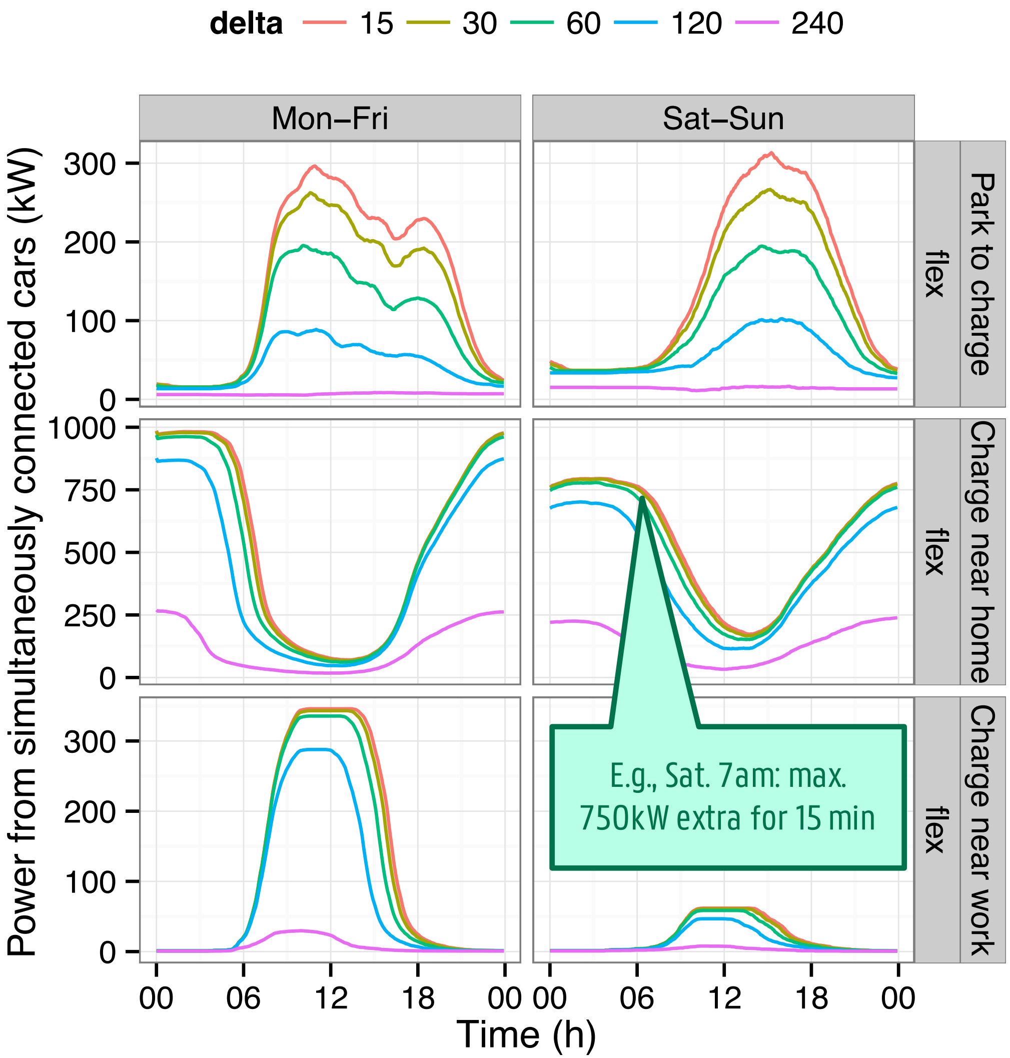
QUANTIFICATION OF FLEXIBILITY: RESULT



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

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BUT … WHAT FLEXIBILITY IS ACTUALLY USED?

Quantification of use of flexibility in relevant use cases:

$$E_{flex} = \frac{\text{Energy beyond } t_{BAU}}{\text{Maximal energy beyond } t_{BAU}} \Rightarrow 1 - E_{flex} = \text{fraction charged at } t_{BAU}$$

$$T_{flex} = \frac{t_{coordinated} - t_{BAU}}{t_{depart} - t_{BAU}} = \text{fraction of idle time exploited to delay}$$

E.g., $E_{flex} = 0.2 \Rightarrow$ only 20% of charge volume is delayed

E.g., Tflex = 0.8 $\Rightarrow$ end-of-charge at 80% of flexibility time window

CASE STUDIES: (1) Load flattening, (2) RES balancing

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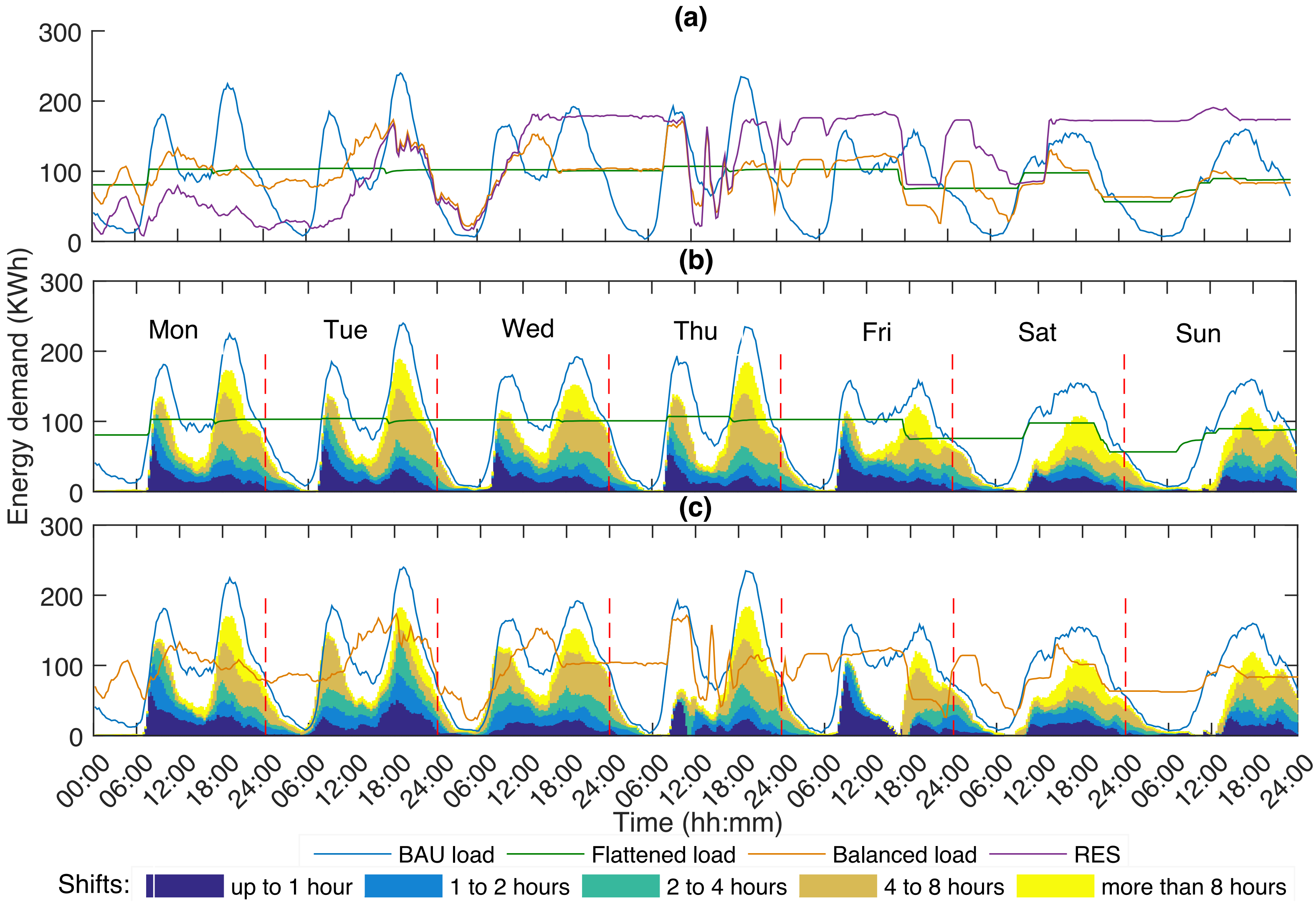
SAMPLE FLEXIBILITY EXPLOITATION: RESULTS



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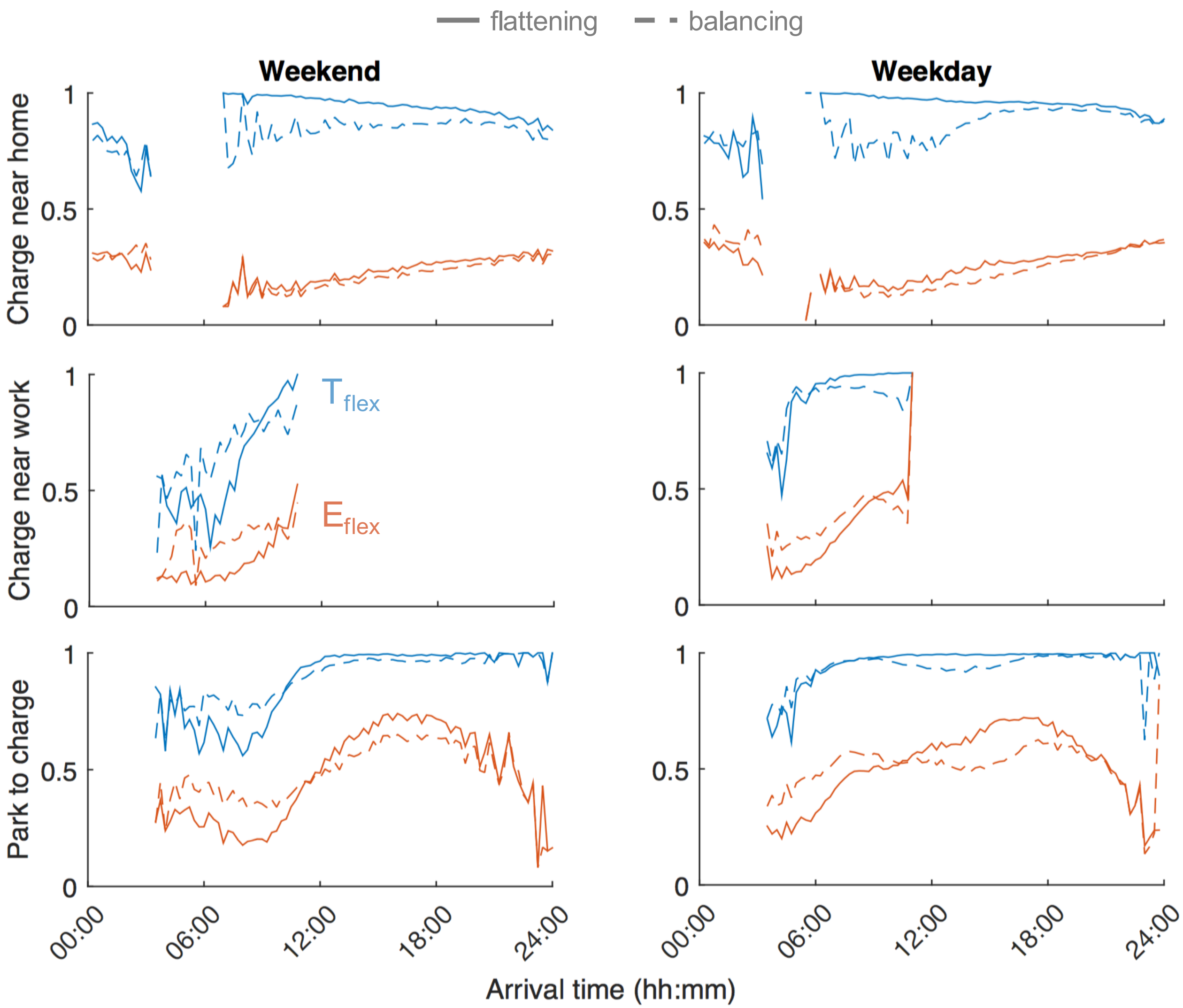

- Near home:
  - T_{flex} close to 1: charging till last moment, but…
  - E_{flex} low: reasonable SoC at t_{BAU}
- Near work:
  - Higher T_{flex} in weekend
  - Reasonable SoC at t_{BAU}
- Park-to-charge:
  - Tf_{lex} close to 1
  - Peaked E_{flex} during daytime

CONCLUSION

- 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 $\Rightarrow$ can have ~7MW extra for 2h

OUTLINE

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, Vol. 179, Oct. 2016, pp. 790-805.

Part I: Algorithms for DSM/DR

- Example 1: Peak shaving
- Example 2: Wind balancing

Part II: Data analytics

- Clustering smart metering data
- EV usage analysis
- Flexible usage of white good appliances

Part III: Non-intrusive load monitoring

- Appliance classification w/ convolutional nets
- Appliance classification w/ elliptical Fourier descriptors

MODELING WHITE GOOD FLEXIBILITY BEHAVIOR

Flexible use of appliances (dishwasher, washing machine, tumble dryer) characterized by

- Time of availability = appliance **configuration time**
- Time window for deferring operation defined by **deadline**
- Amount of deferrable energy = depending on device

Gap: data-driven modeling & real-world flexibility assessment

1. Real-world data?
2. Statistical models of sojourn vs time spent charging?
3. What amount of power can we shift over how much time?

SAMPLE RESULT FOR DISHWASHER – MODEL 1

Two-stage: (i) deadline G-means clustering, (ii) fit K-component finite mixture using MCMC estimation of distribution parameters

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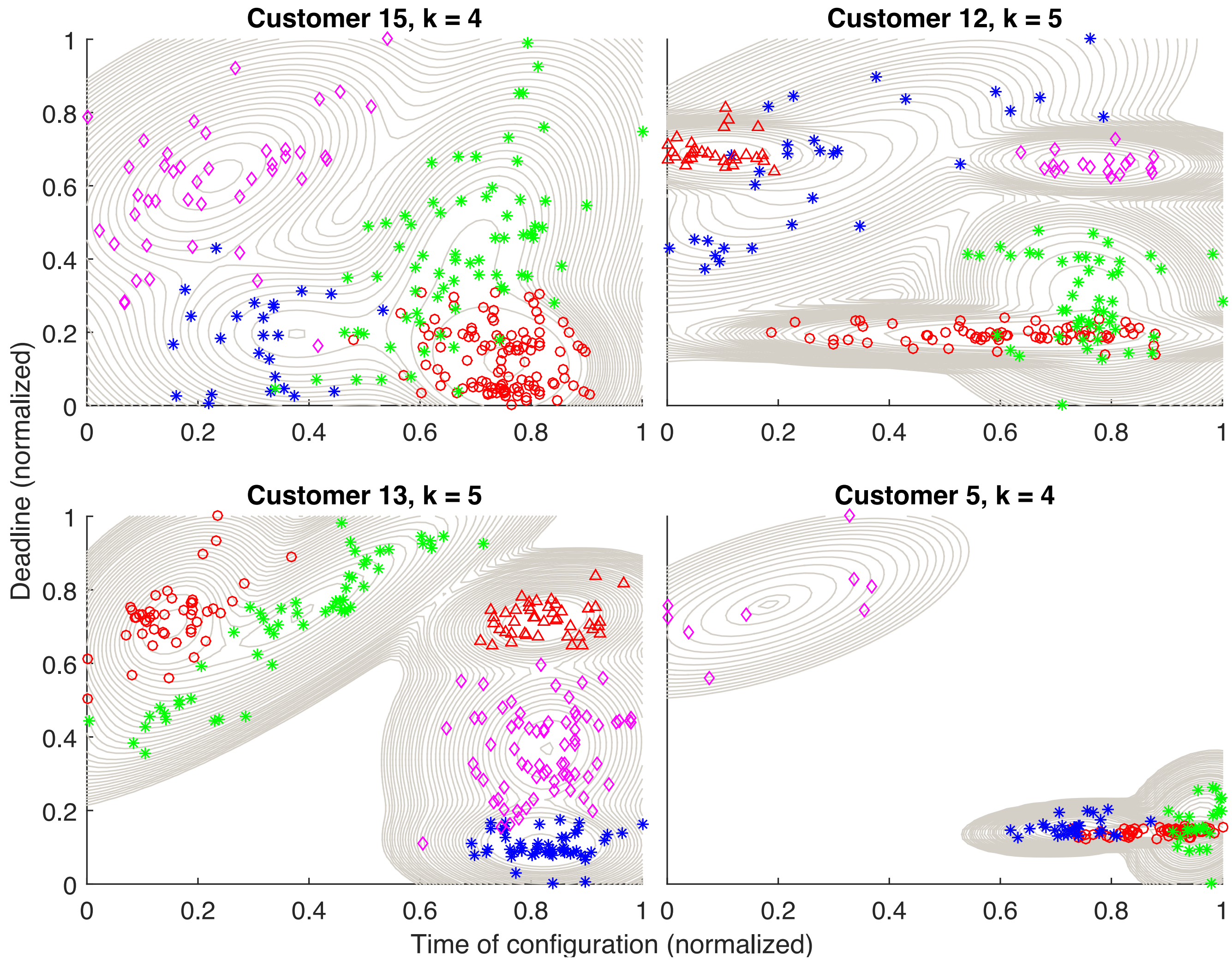
SAMPLE RESULT FOR DISHWASHER – MODEL 2

Single-stage: reorder X-axis, then fit with 2D Gaussian Mixture Model (GMMs)



C. Develder, et al., "Algorithms for Smart Grids: Knowing and controlling power consumption", IEC Workshop, Paris, France, 19-20 Oct. 2017

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CONCLUSIONS

- First model based on real-world dataset of flexible appliance usage
- Two models: (1) two-stage univariate modeling, (2) single-stage bivariate distribution fitting with GMMs
- Validation confirms Model 2 suitability for three device types
  (using k-s test on empirical distribution from data vs model-generated samples)
- Exploration of influential factors: holidays, week vs weekend, seasons $\Rightarrow$ user-dependent!

OUTLINE

L. De Baets, J. Ruyssinck, C. Develder, T. Dhaene and D. Deschrijver, **"Appliance classification using VI trajectories and convolutional neural networks"**, Energy Build., Vol. 158, Jan. 2018, pp. 32-36. (In Press)

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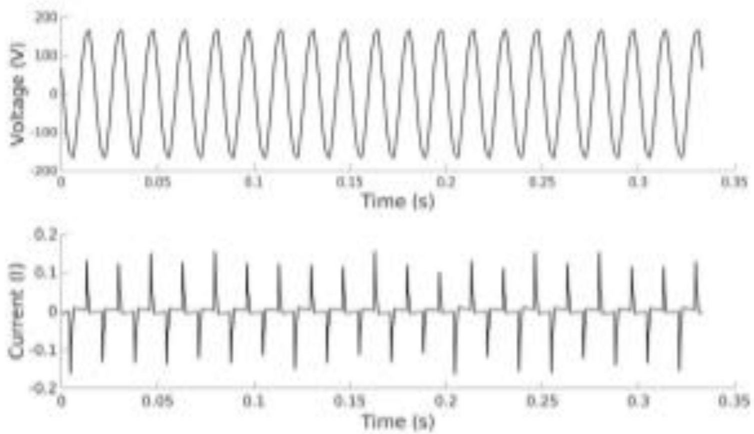
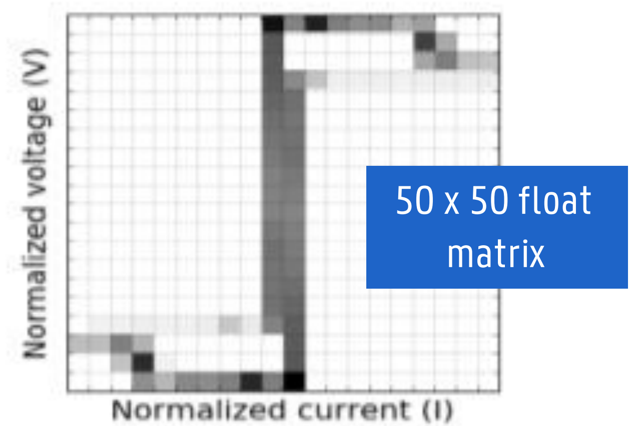
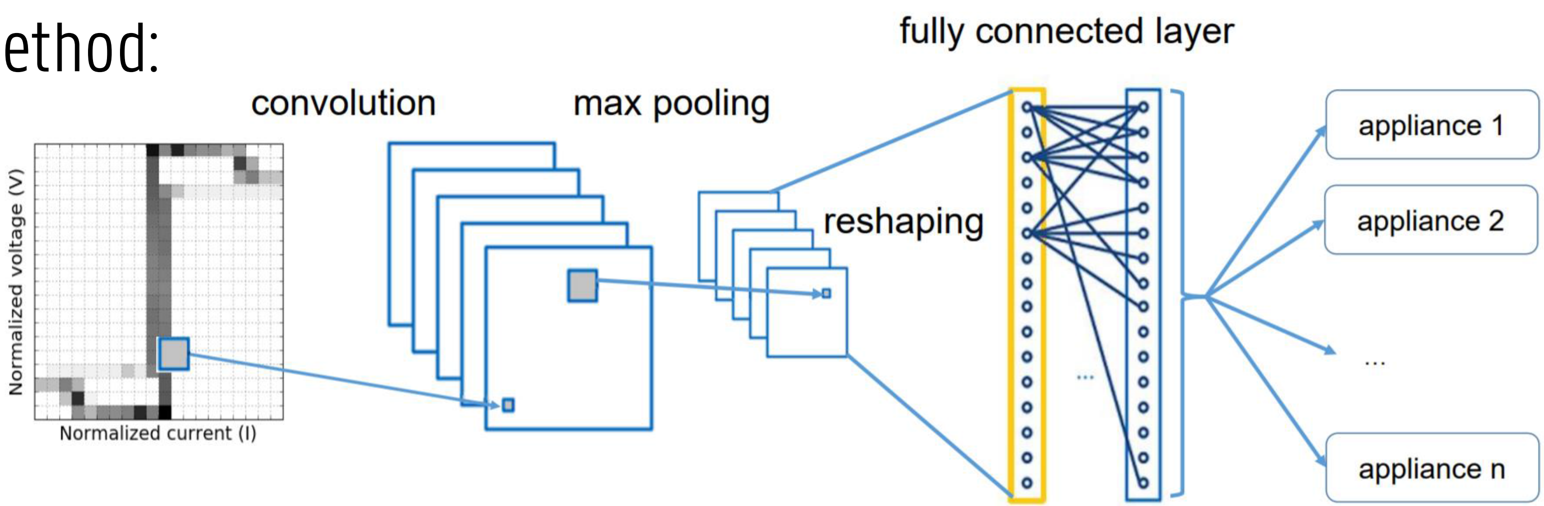
CLASSIFICATION w/ VI TRAJECTORIES & CONVNETS

- Input:





- Method:



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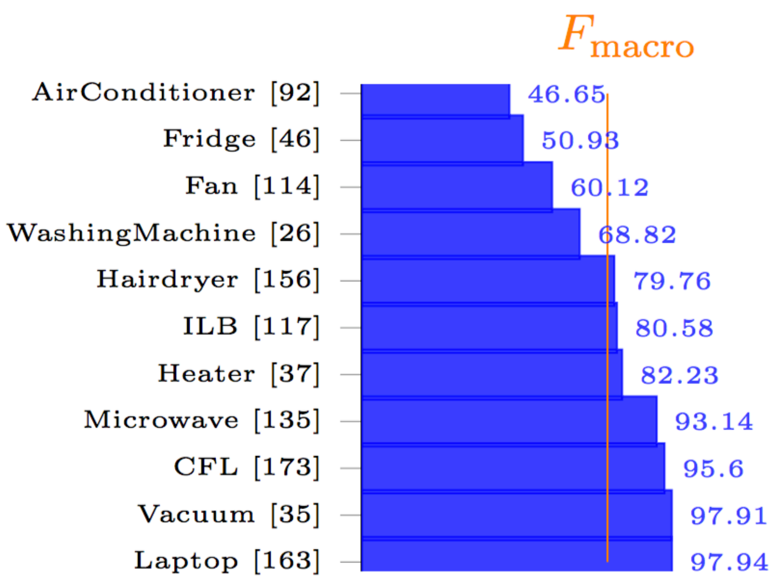
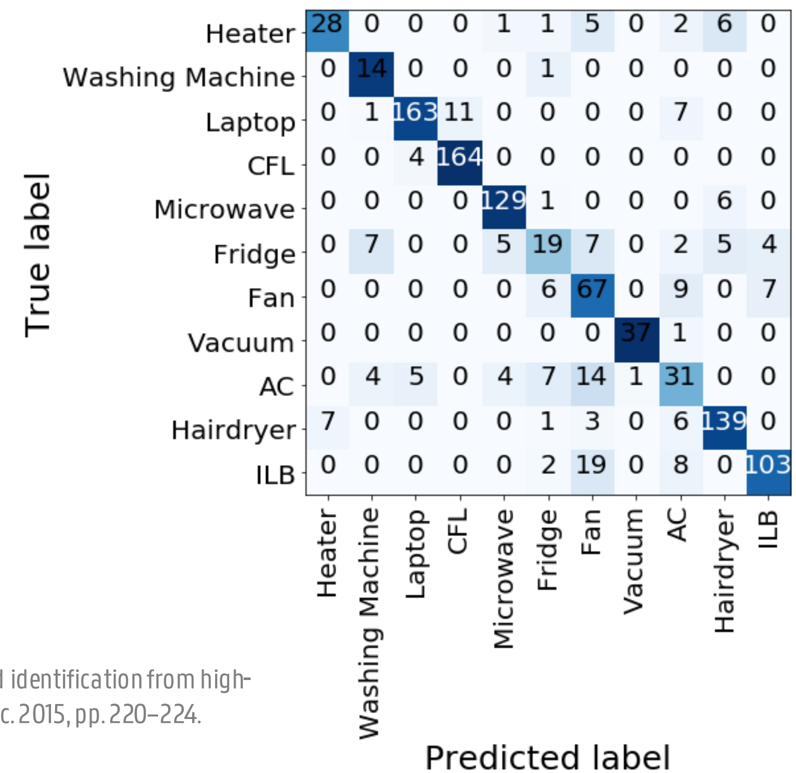
APPLIANCE CLASSIFICATION RESULTS – VI AS IMAGE

- **PLAID dataset:** 11 device types, 55 households, submetered @ 30kHz
- **Evaluation:** leave-one-house-out cross-validation

$\Rightarrow F_{macro} = 77.10\%$ (beating SotA* of 70.41%)





*: J. Gao, E. C. Kara, S. Giri, and M. Bergés, "A feasibility study of automated plug-load identification from high-frequency measurements," in Proc. IEEE GlobalSIP 2015, Orlando, FL, USA, 14-16 Dec. 2015, pp. 220–224.

OUTLINE

L. De Baets, C. Develder, D. Deschrijver and T. Dhaene, **"Automated classification of appliances using elliptical fourier descriptors"**, in Proc. IEEE Conf. Smart Grid Commun. (SmartGridComm 2017), Dresden, Germany, 23-26 Oct. 2017.

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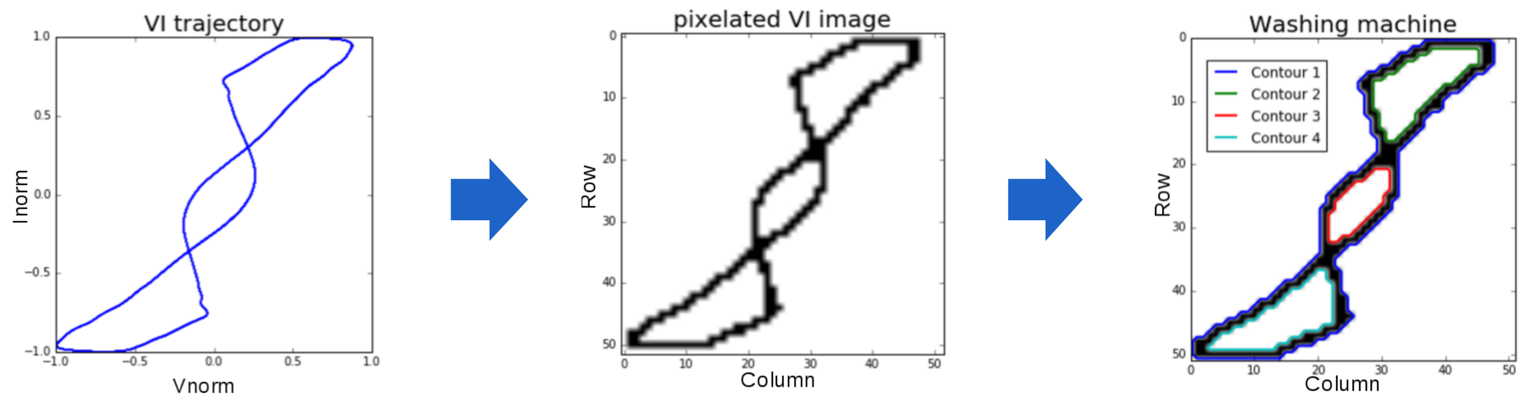
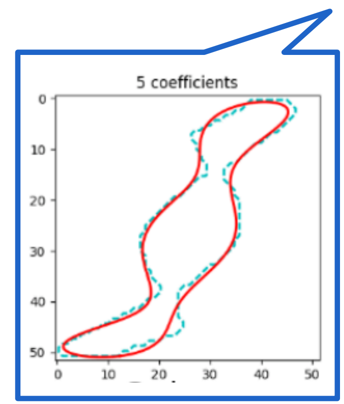
CLASSICATION w/ VI & FOURIER DESCRIPTORS



- Convert normalized VI trajectory to contours
- Approximate contours with elliptical Fourier descriptors (EFDs)
- Classify with NN using EFDs as input



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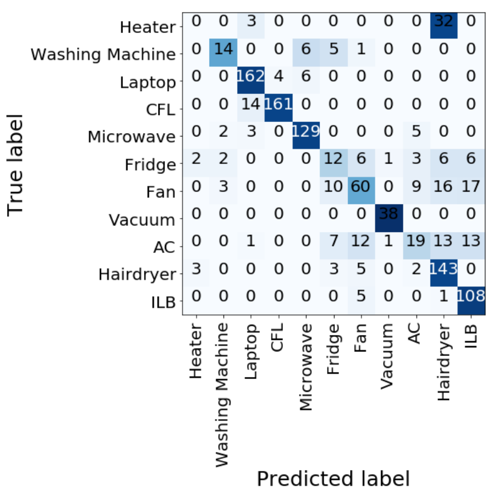
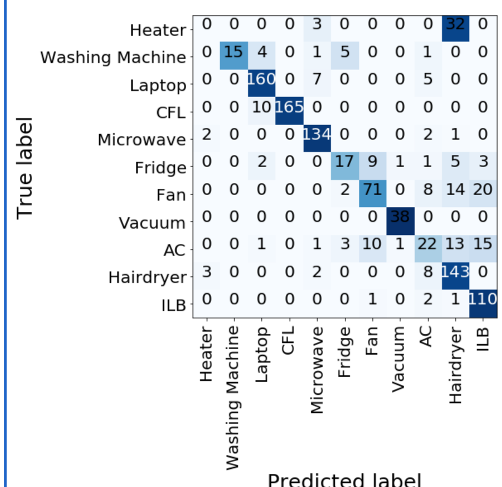
APPLIANCE CLASSIFICATION RESULTS

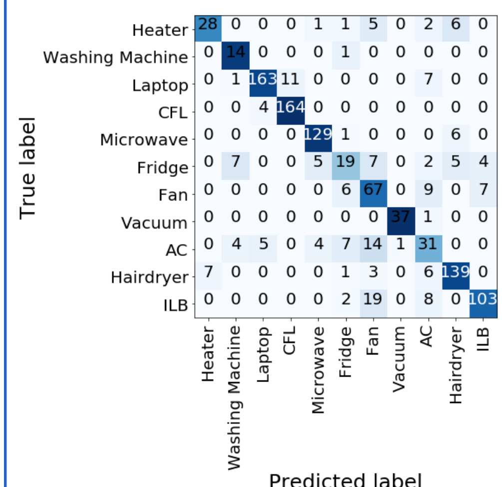
- **PLAID dataset:** 11 device types, 55 households, submetered @ 30kHz
- **Evaluation:** leave-one-house-out cross-validation

	Gao et al. 2015	Fourier descriptors	VI greyscale image
Input	16 x 16 binary	3 x 4 float	50 x 50 float
Accuracy	81.75%	77.14%	84.55%
macro-F1	70.41%	65.80%	77.10%

Confusion







C. Develder, et al., "Algorithms for Smart Grids: Knowing and controlling power consumption", IEC Workshop, Paris, France, 19-20 Oct. 2017

CONCLUSION

L. De Baets, J. Ruyssinck, C. Develder, T. Dhaene and D. Deschrijver, **"Optimized statistical test for event detection in non-intrusive load monitoring"**, in Proc. IEEE Int. Conf. Environment and Electr. Eng. and IEEE Industrial and Commercial Power Sys. Europe (EEEIC / I&CPS Europe), 6-9 Jun. 2017.

- VI images as greyscale images & convolutional NNs beats previous state-of-the-art
- Fourier descriptor approach is viable alternative: lower performance, but much simpler features & computationally more efficient

Further NILM building blocks:

- **Event detection**: detect when device turning on/off (or changing state?)
- **Novel appliance detection**: devices come and go – avoid manual (re)labeling
- **Program cycle** detections (e.g., washing machines)
- ...

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WRAP-UP

Summary

- Challenge: deal with renewable sources
- Demand response algorithms: initial feasibility studies
- Get insight in consumption/production: e.g., clustering as first step
- Quantify flexibility, e.g., the EV case study
- Pieces of the NILM puzzle: classification, event detection, ...
- What's next?
  - Can we **learn/predict** flexibility, e.g., from smart metering data?
  - Can we infer **user behavior**, and then (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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