Electric Load Disaggregation as a Means for Increasing Energy Awareness and Reducing Energy Consumption

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Public Lecture Series: Sustainability in Computer Science

Introduction and Overview

- We are using energy in various forms in our daily life, at work, and via machines
- Especially when not produced from renewable sources, this is a signifcant problem for sustainable living
- What can we do as computer scientists to help?
  (Apart from turning off our computers)
- This talk describes one way how this question can be addressed
- We will use computers, smart meters, algorithms and datasets

Smart Meter Rollout

- Energy Services Directive (2006/32/EC) and the electricity directive (2009/72/EC) require the implementation of "intelligent metering systems".
- Such systems ought to be in place for 80% of electricity consumers by end 2020
- The number of electricity meters potentially required to be replaced over the coming decade made standardization work urgent

Transistion towards smart meters

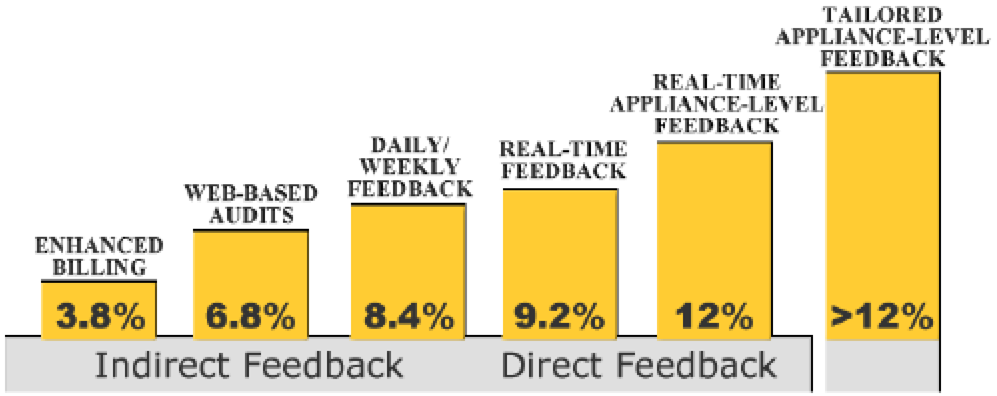
Current billing

- Problem: consumption information is connected to billing
  - Much later than consumption occurred
  - No clue on how energy was used
  - Even worse: in Austria you often pay an estimated bill which is corrected afterwards

http://i.telegraph.co.uk/

Strategies for domestic energy conservation

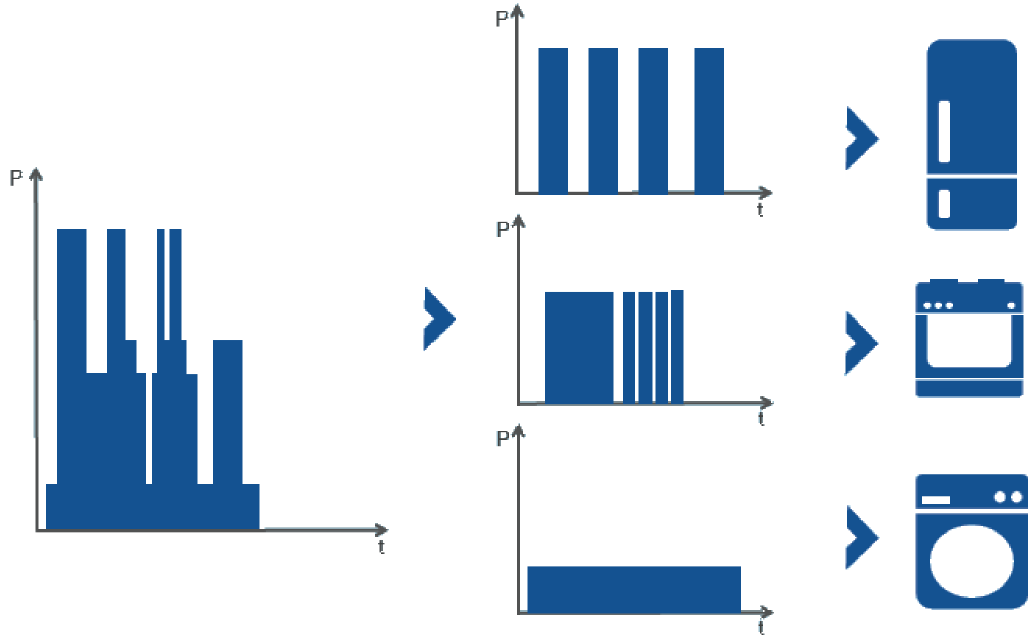
- **Energy audits:** analyzing energy use to provide tips
- **Smart metering:** more frequent meter reading and reporting (e.g. Italy)
- **Prepaid billing:** average savings of 11% in UK
- **Adaptive tariff plans:** incentive users to operate in off-peak periods
- **Persuasive interfaces:** supporting users in understanding energy usage



A. Monacchi, W. Elmenreich, Salvatore D'Alessandro, and A. Tonello. Strategies for domestic energy conservation in Carinthia and Friuli-Venezia Giulia. In Proceedings of the 39th Annual Conference of the IEEE Industrial Electronics Society (IECON 2013). IEEE, November 2013.

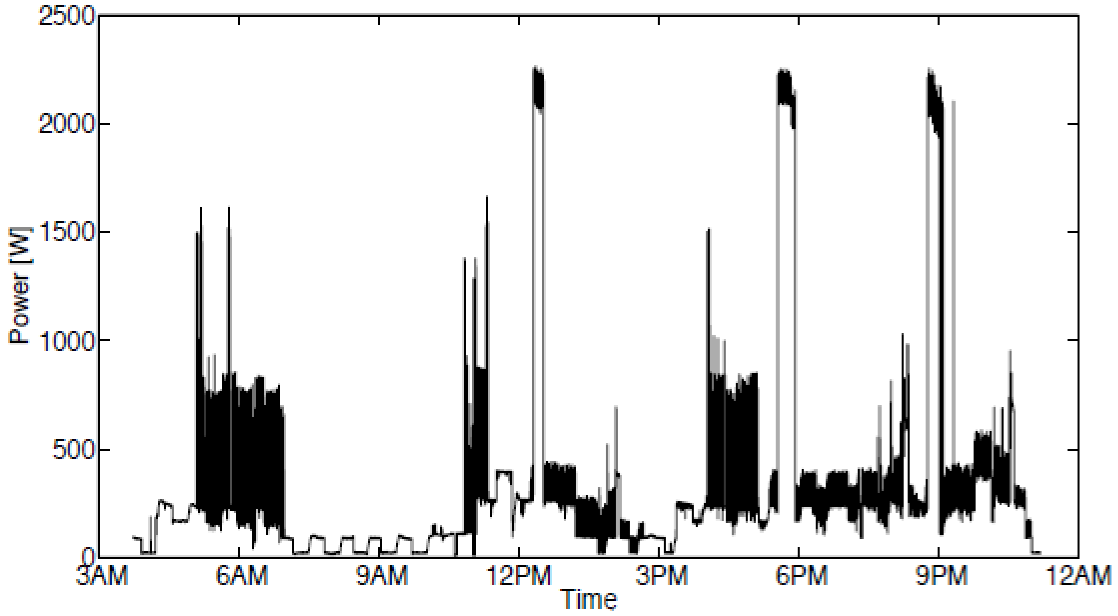
Privacy concerns

- Frequent measurement of power allows for
  - Infering about daily schedule
  - Identifying time and type of used devices
  - Can be used for good and evil



Power consumption as information

- A power draw is an information, e.g. on/off
  - Aggregated power draw measured at smart meter

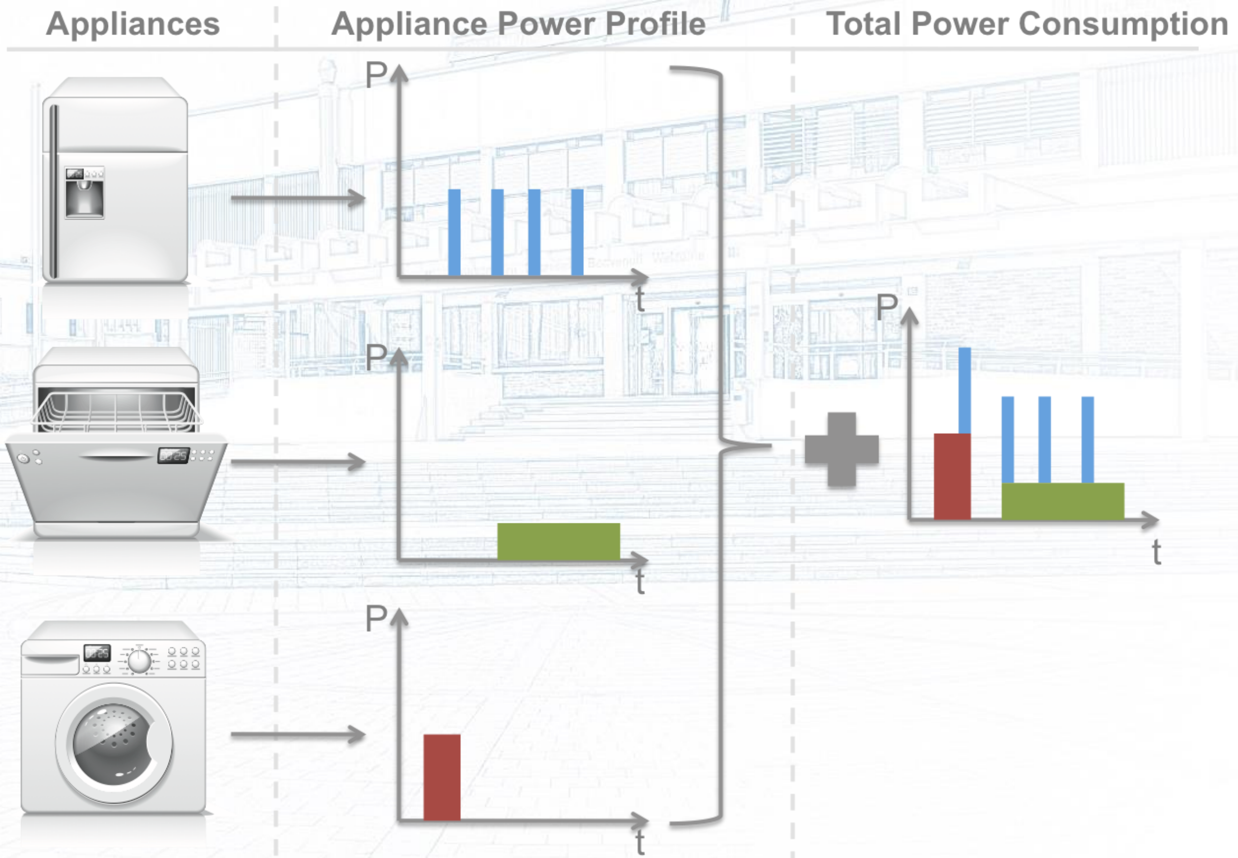


  - Can we disaggregate power draws?

→ Non-Intrusive load monitoring

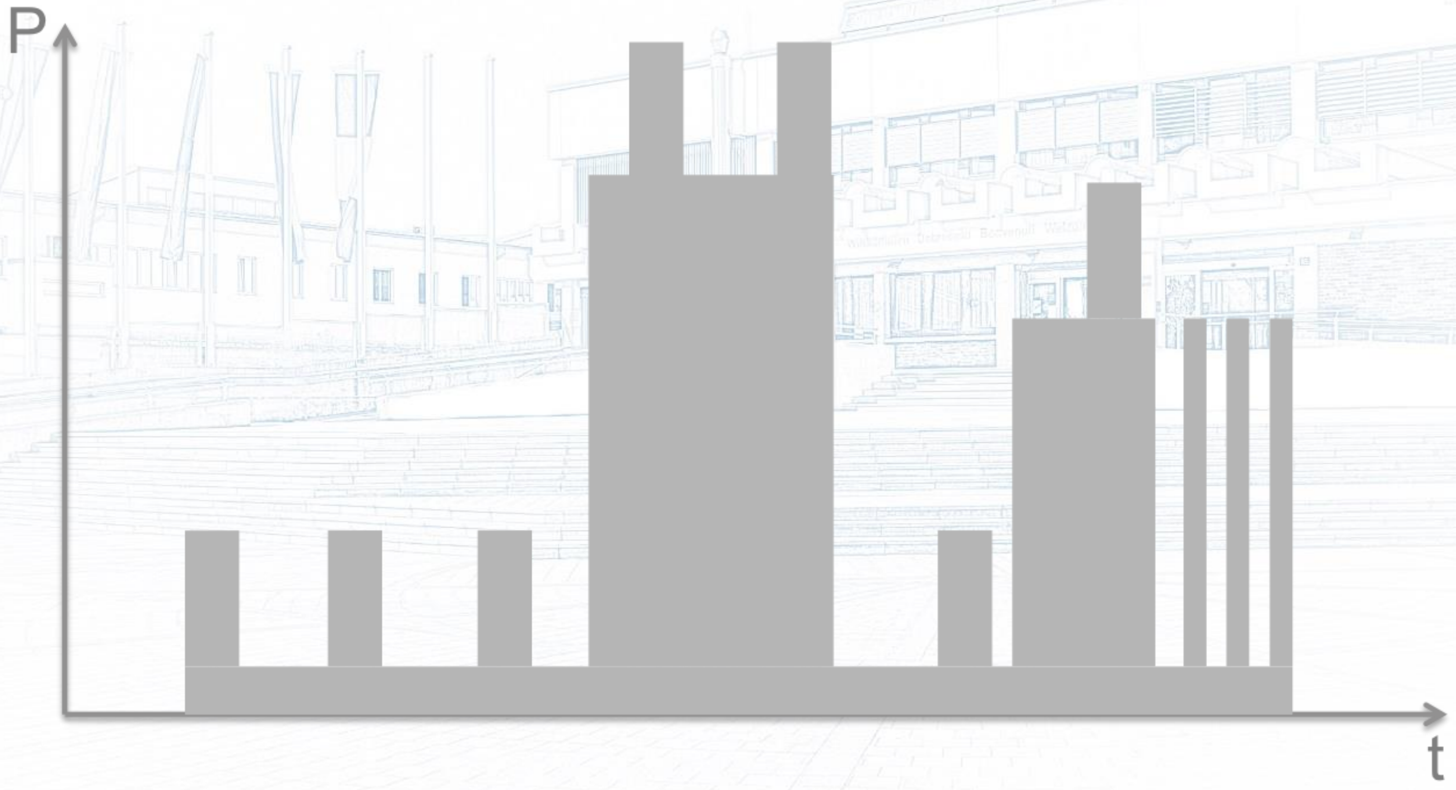
Non-Intrusive Load Monitoring

- (How) can devices be detected based on their energy signature?



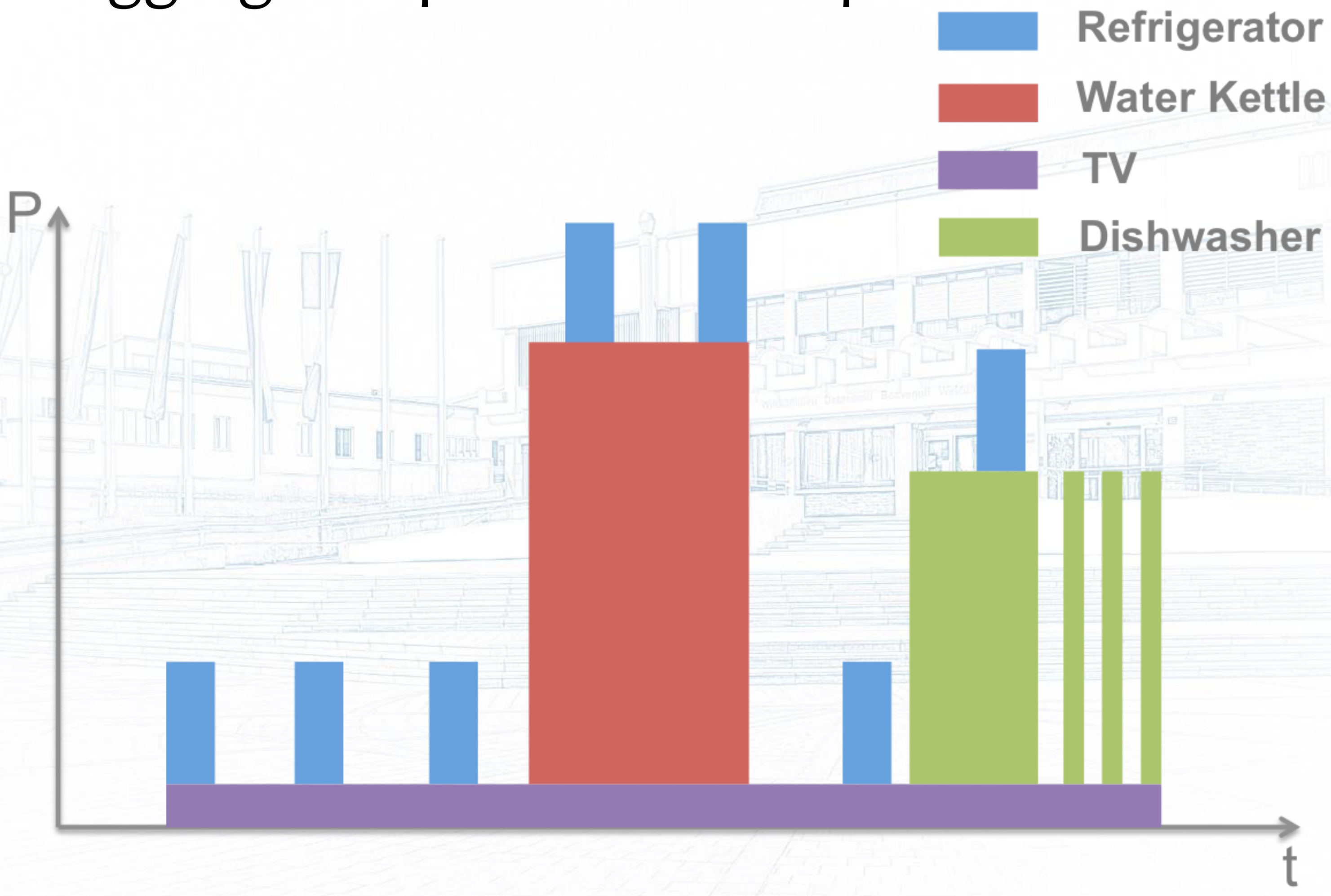
Non-Intrusive Load Monitoring

- Power consumption over time



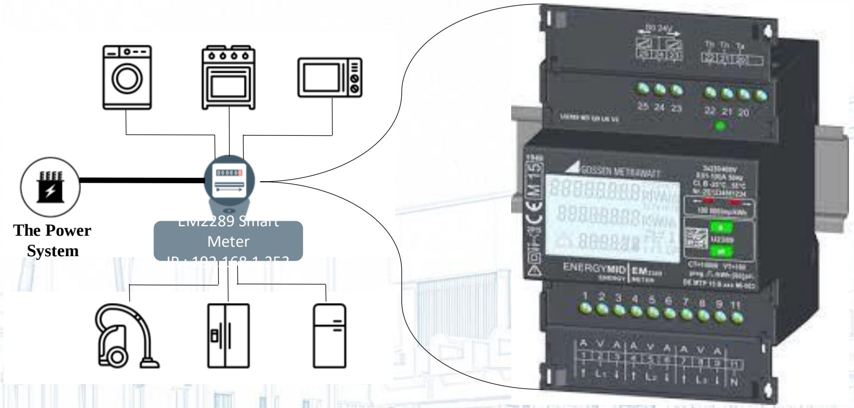
Non-Intrusive Load Monitoring

- Disaggregated power consumption

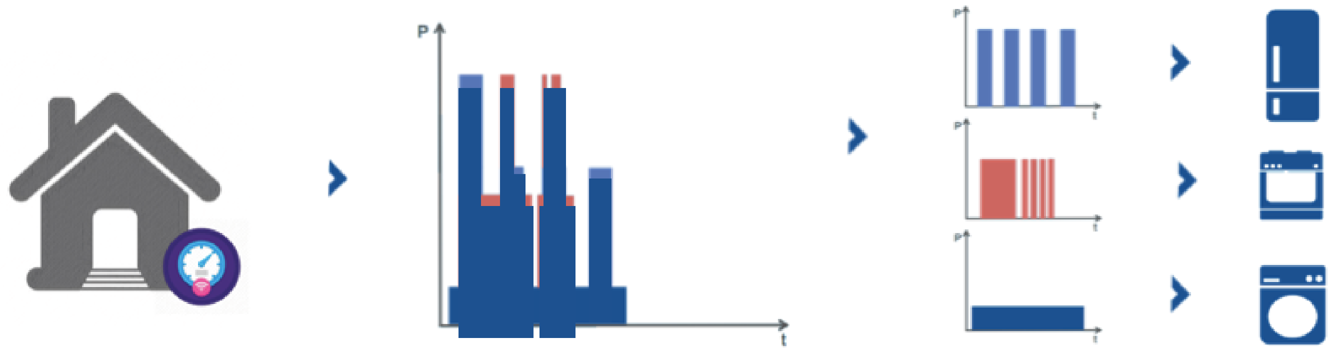


Non-Intrusive Load Monitoring

- Non-intrusive Load monitoring (NILM): Monitor devices with a central meter



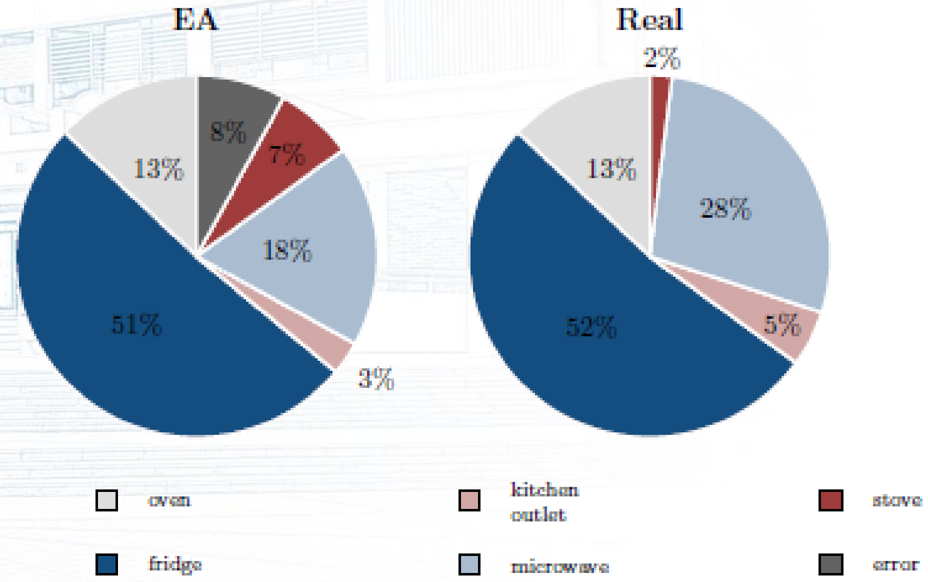
- Load Disaggretation: Split up consumption into different appliances



George Hart. Non-intrusive appliance monitor apparatus. Patent application, August 1989

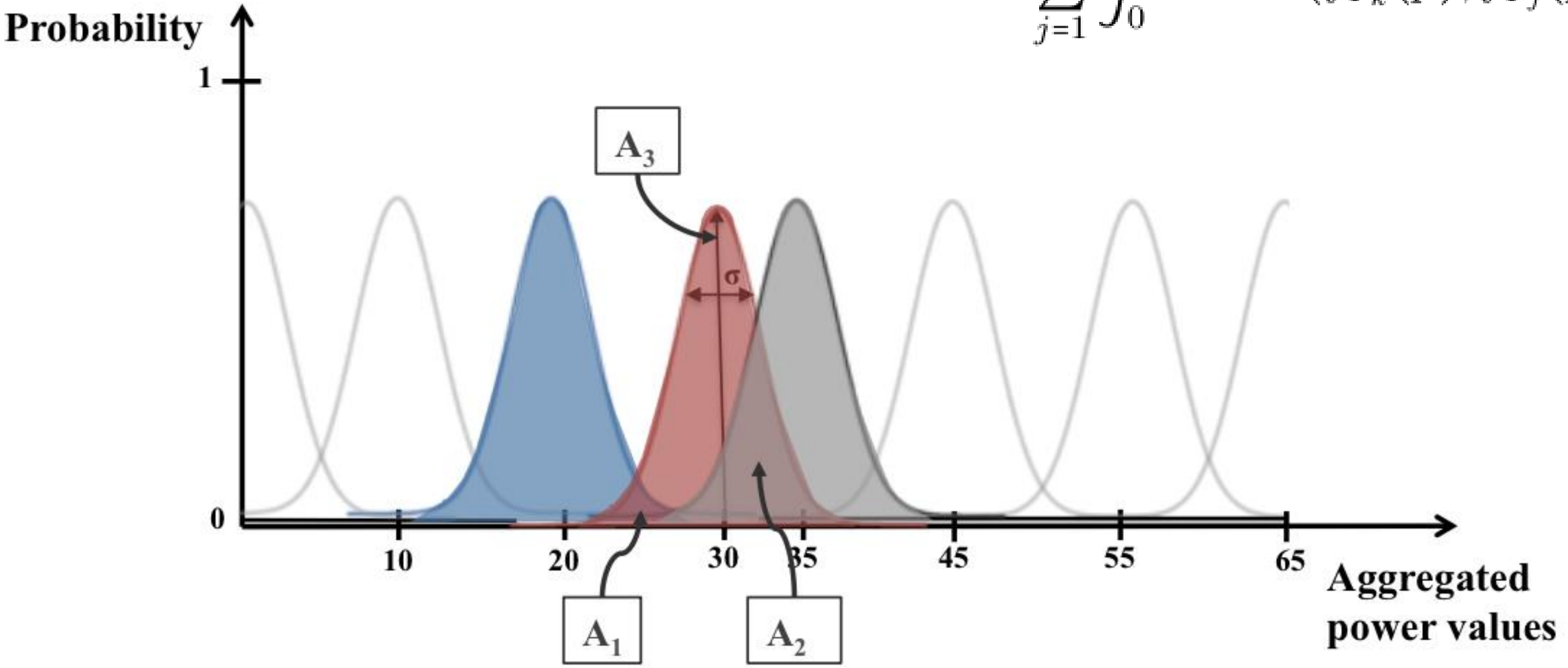
First Idea: Model as Knapsack problem

- From your set of available devices find a subset that matches measured consumption as close as possible
- Problems
  - Large search space (requires heuristic search)
  - Ambiguous combinations possible
  - Results can change much upon a small overall power change
- Works only for low number of devices

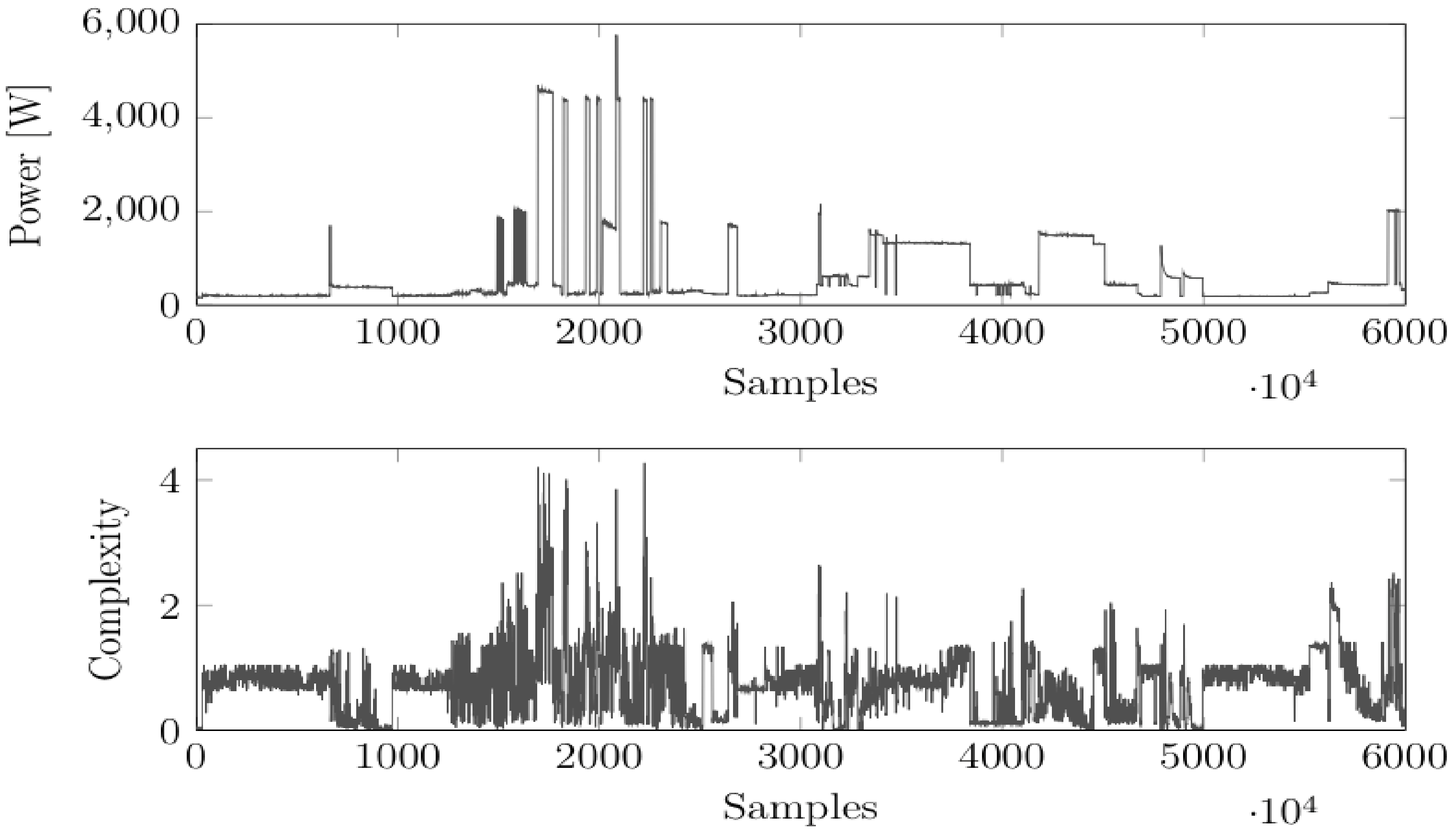


Appliance Set Complexity

$$C_k = \sum_{j=1}^{M} \mathrm{OVL}(f_{P_k}, f_{P_j})$$
$$= \sum_{j=1}^{M} \int_0^{P_M} \min(f_{P_k}(p), f_{P_j}(p))\mathrm{d}p$$

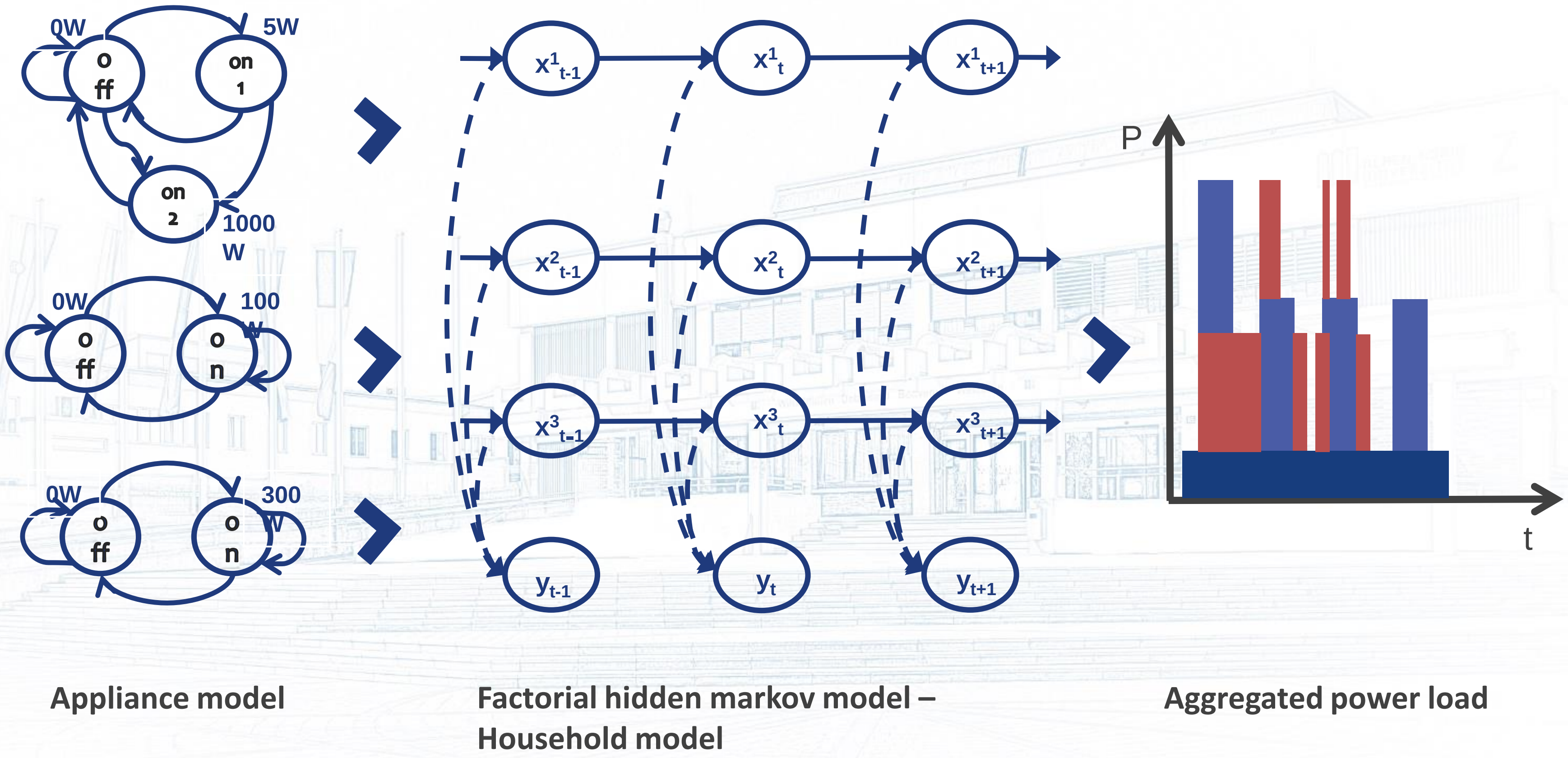


Appliance Set Complexity



$$C_{total} = \frac{1}{T}\sum_{t=1}^{T} C_t = \frac{1}{T}\sum_{t=1}^{T}\sum_{k=1}^{M} \mathrm{OVL}(f_{P_t}, f_{P_k})$$

Particle Filter Based **L**oad **Di**saggregation
PALDI



D. Egarter, V. P. Bhuvana, and W. Elmenreich. PALDi: Online load disaggregation via particle filtering. *IEEE Transactions on Instrumentation and Measurement*, 64:467–477, February 2015.

Deep Learning Approaches

- Model problem as a classification problem
- Input data is a sequence of previously measured power
- Train a classifier using machine learning
- Requires a sufficiently large dataset
- Black box, but results excel

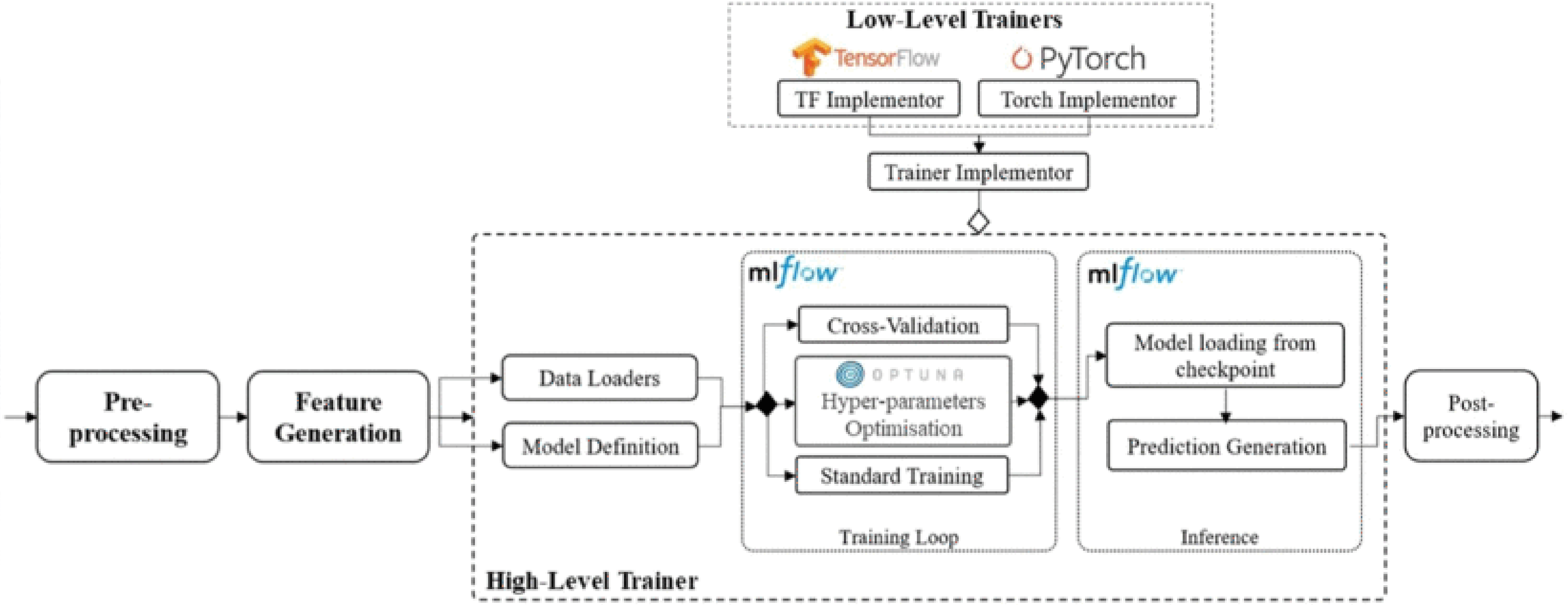
```
t = time.time()
clf = RandomForestClassifier(max_depth=10, n_estimators=50, random_state=0).fit(X_train, y_train_x[i])
print("learning time: " + str(time.time()-t))
t = time.time()
print("score: " + str(clf.score(X_test, y_test_x[i])))
print("evaluation time: " + str(time.time()-t))
print("")

t = time.time()
clf = LogisticRegression(random_state=0, max_iter=200000).fit(X_train, y_train_x[i])
print("learning time: " + str(time.time()-t))
t = time.time()
print("score: " + str(clf.score(X_test, y_test_x[i])))
print("evaluation time: " + str(time.time()-t))
print("")
```

TABLE I
COMPARING THE SCORES OF ALL DEVICES FOR EACH CLASSIFIER. RUNTIMES ARE MEASURED ON A AMD RYZEN 7 PRO 5850U. RUNTIMES ON AS RASPBERRY PI ARE EXPECTED TO BE UNDER 10 SECONDS.

		Score	Evaluation/Training Time
MLPClassifier	all devices	0.26666	≤ 1 sec
KNeighborsClassifier	fan	0.73333	≤ 1 sec
	hairdryer	1.00000	
	lamp	0.76666	
	vacuum	0.86666	
	kettle	0.86666	
AdaBoostClassifier	fan	0.8	≤ 1 sec
	hairdryer	1.0	
	lamp	0.9	
	vacuum	0.9	
	kettle	0.86666	
RandomForestClassifier	fan	0.73333	≤ 1 sec
	hairdryer	1.0	
	lamp	0.76666	
	vacuum	0.86666	
	kettle	0.86666	
LogisticRegression	fan	0.5	≤ 1 sec
	hairdryer	1.0	
	lamp	0.76666	
	vacuum	0.63333	
	kettle	0.73333	

Deep-NILMTK Pipeline

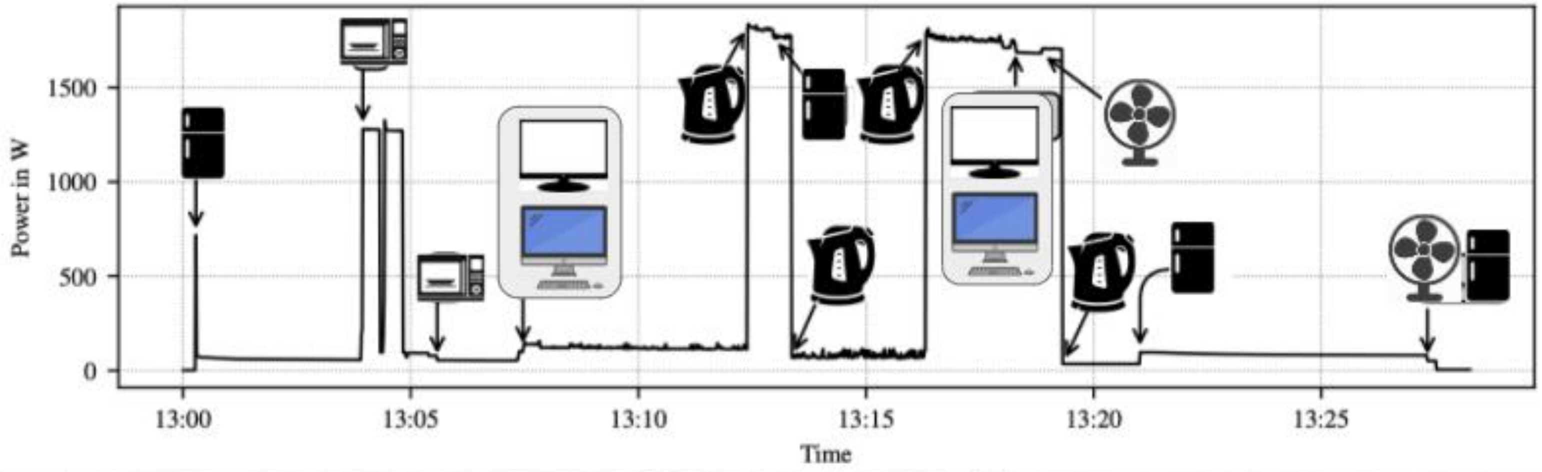
- Modular concept, only new parts need to be implemented
- Standardized evaluation framwork



Hafsa Bousbiat, Anthony Faustine, Christoph Klemenjak, Lucas Pereira, and Wilfried Elmenreich. Unlocking the full potential of neural NILM: On automation, hyperparameters & modular pipelines. *IEEE Transactions on Industrial Informatics*, pages 1–9, 9 2022

Automatic Labelling of Appliance’s Events

- Simulation of typical household devices
- On/Off events of some appliances are easier to detect than others.
- Possibility to reveal routines of residents.



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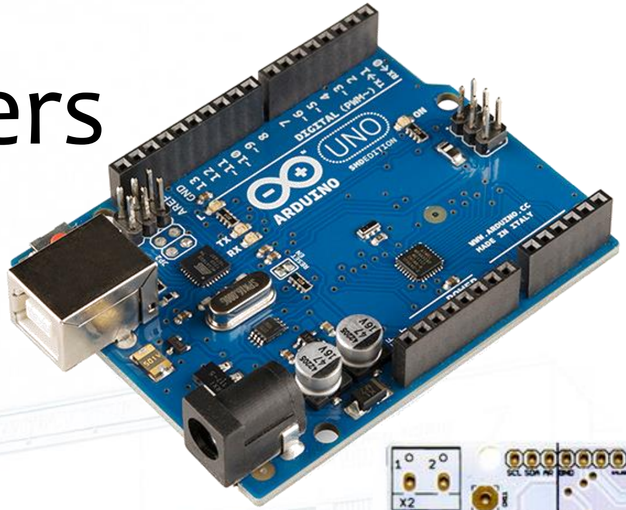
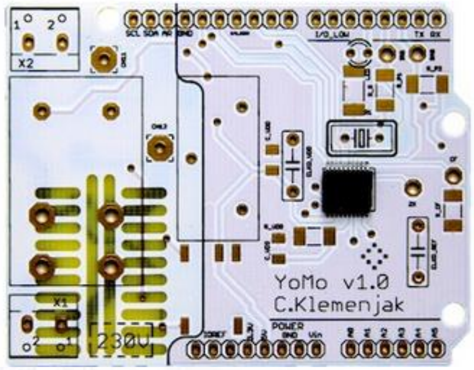
Private smart metering

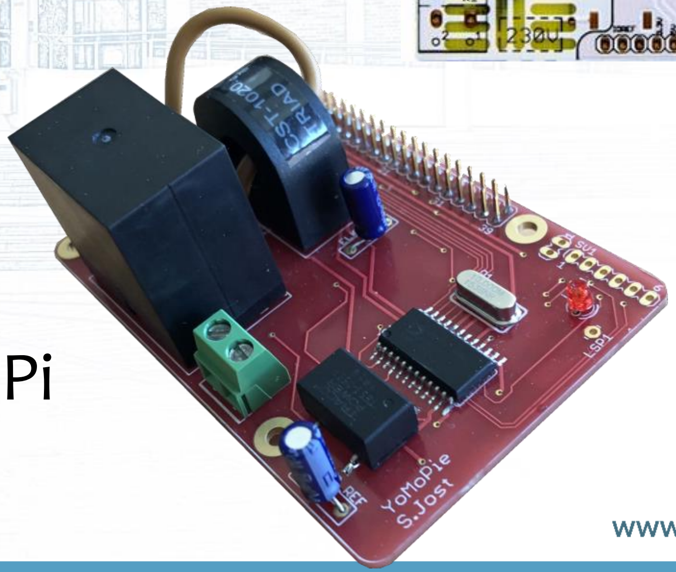
- Measuring energy consumption for own applications
  - Monitor own energy consumption
  - Identifying energy-hungry devices
  - Optimize energy consumption with a PV systems‘s production
  - Smart homes and ambient assisted living,
    e.g., support independent living of elderly people
- Market for private power meters
- Open hardware design

YoMo and YoMoPie Smart Meters

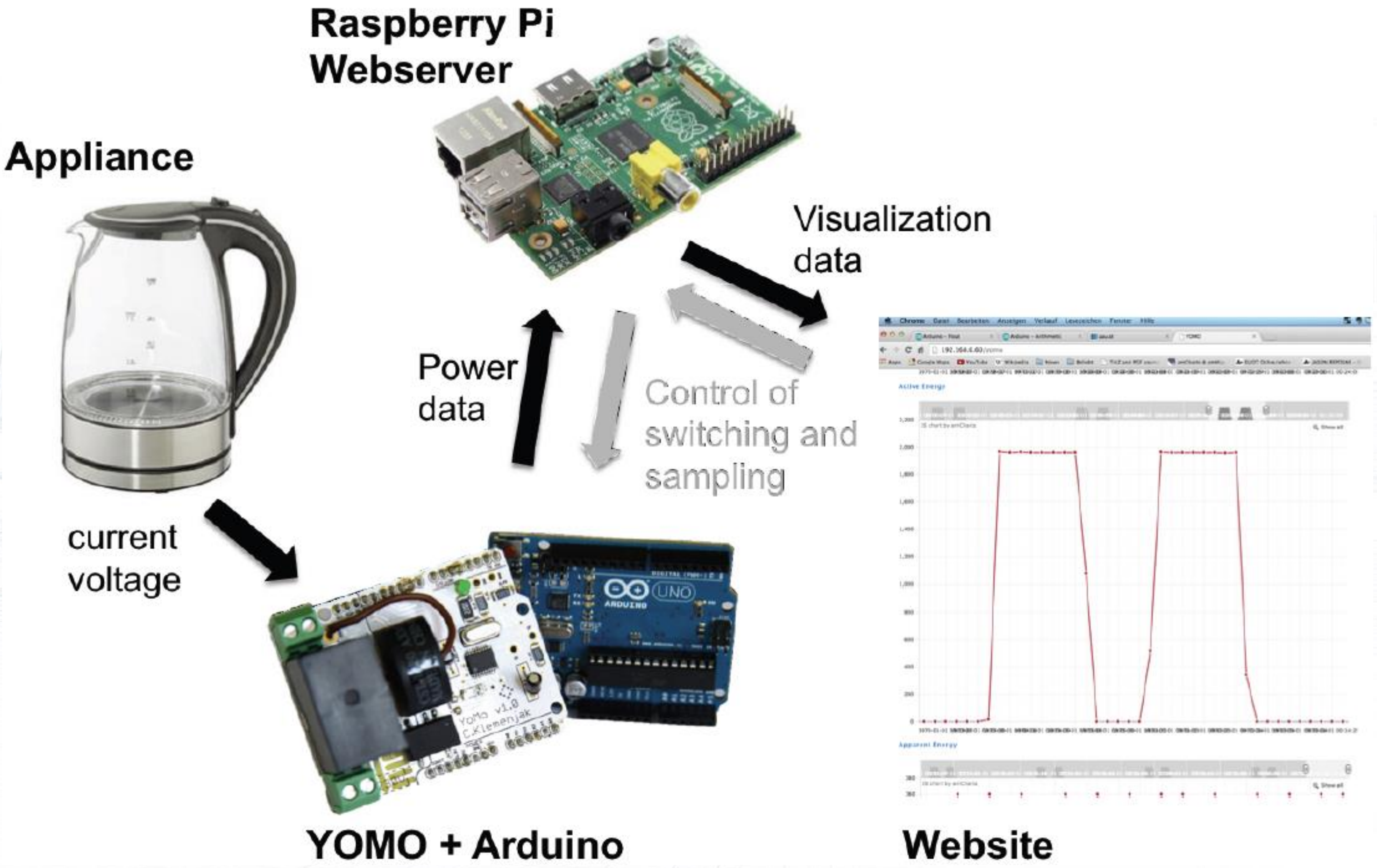


- YoMo: Designed as Arduino Shield for
  - industry and researchers to
  - create new energy system applications
- Open-Source & Open-Hardware
  - Schematics and PCB design are publicly available
- Low Cost
  - Overall parts cost 30€
  - Production cost including parts and assembly: 90 €
  - No license fees
- YoMoPie: same extension, but for RaspBerry Pi





Smart Metering System with YOMO



Training and Evaluation

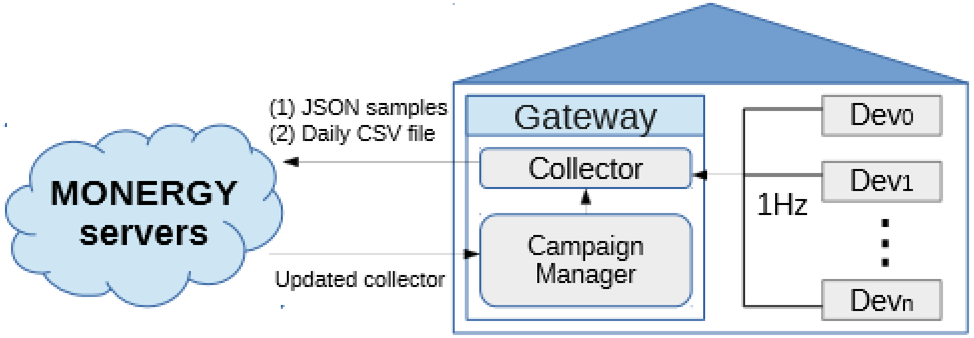
- We need datasets with realistic and sufficient power recordings
- Requirements
  - Similar geographic region
  - Measurement frequency
  - Individually measured devices (ground truth)
  - Sufficient duration of measurement campaign (spanning seasons)
- Households (… size) vs. office vs. industry environments

Example Datasets

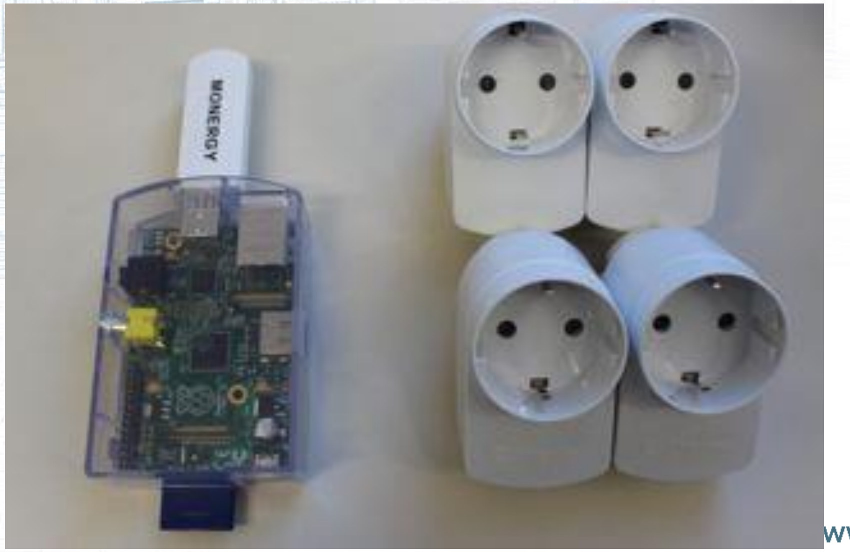
Dataset	Location	Duration	#Houses	#Sensors (per house)	Features	Resolution
ACS-F1 [7]	Switzerland	1 hour session (2 sessions)	N/A	100 devices in total (10 types)	I, V, Q, f, Φ	10 secs
AMPds [8]	Greater Vancouver	1 year	1	19	I, V, pf, F, P, Q, S	1 min
BLUED [5]	Pittsburg, PA	8 days	1	Aggregated	I, V, switch events	12 Khz
GREEND	Austria, Italy	1 year (3-6 months completed)	9	9	P	1 Hz
HES	UK	1 month (255 houses) - 1 year (26 houses)	251	13-51	P	2 min
iAWE [9]	India	73 days	1	33 sensors (10 appliance level)	V, I, f, P, S, E, Φ	1 Hz
IHEPCDS[1]	France	4 years	1	3 circuits	I, V, P, Q	1 min
OCTES[2]	Finland, Iceland, Scotland	4-13 months	33	Aggregated	P, Energy price	7 secs
REDD [4]	Boston, MA	3 - 19 days	6	9-24	Aggregate: V, P; Sub-metered: P	15 Khz (aggr.), 3 sec (sub)
Sample dataset[3]	Austin, TX	7 days	10	12	S	1 min
Smart* [10]	Western Massachussets	3 months	1 Sub-metered +2 (Aggregated + Sub-metered)	25 circuits, 29 appliance monitors	P, S (circuits), P (sub-metered)	1 Hz
Tracebase [6]	Germany	N/A	15	158 devices in total (43 types)	P	1-10 sec
UK-DALE [11]	UK	499 days	4	5 (house 3) - 53 (house 1)	Aggregated P, Sub P, switch-status	16 Khz (aggr.), 6 sec (sub.)

Measurement campaign for GreenD

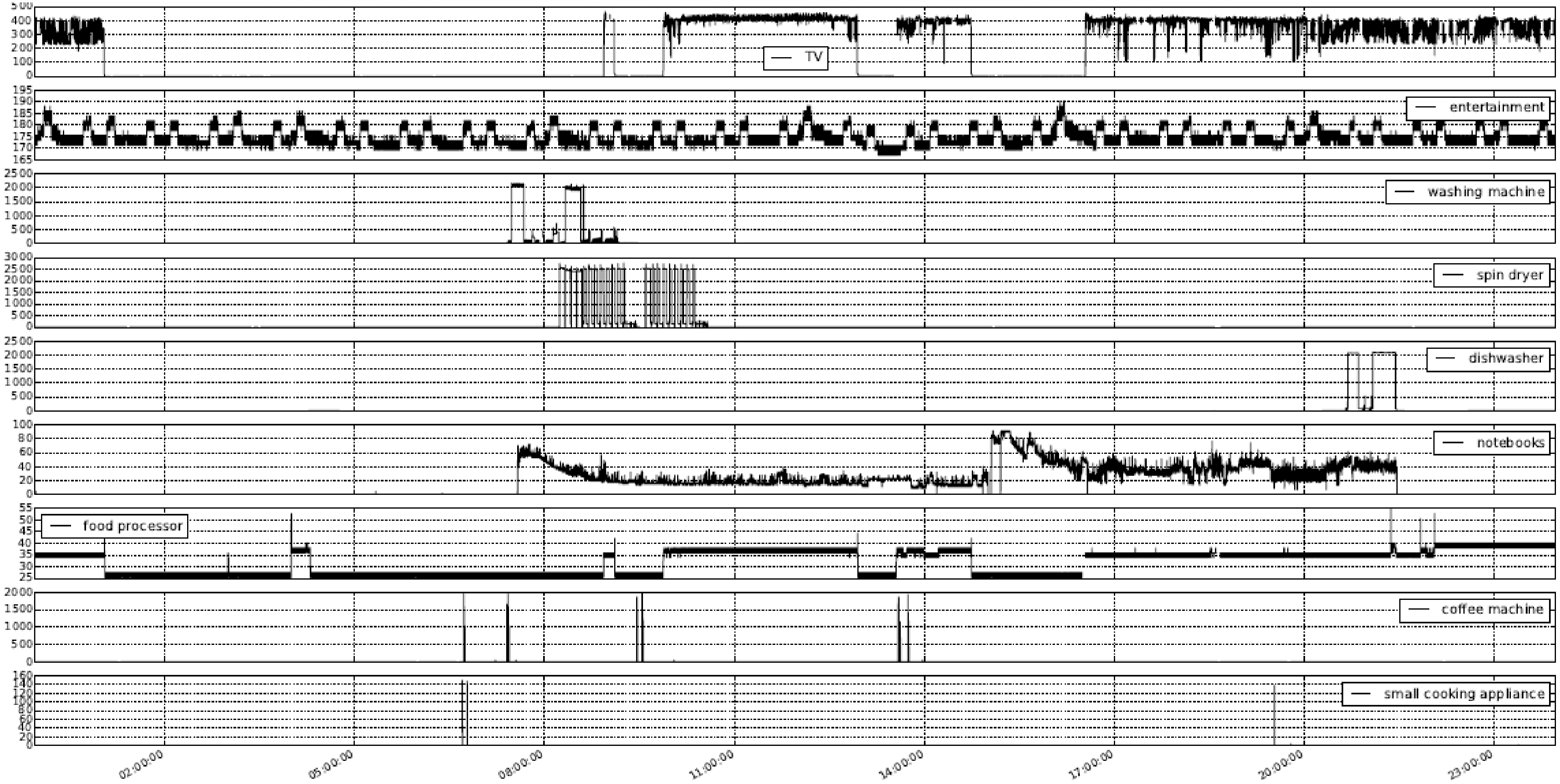
- Power Sensors: Plugwise System (9 outlets)
- Gateway: Raspberry Pi
- Cloud-based webservice



House	Devices
0	Coffee machine, washing machine, radio, water kettle, fridge w/ freezer, dishwasher, kitchen lamp, TV, vacuum cleaner
1	Radio, freezer, dishwasher, fridge, washing machine, water kettle, blender, network router
2	Fridge, dishwasher, microwave, water kettle, washing machine, radio w/ amplifier, dryier, kitchenware (mixer and fruit juicer), bedside light
3	TV, NAS, washing machine, drier, dishwasher, notebook, kitchenware, coffee machine, bread machine
4	Entrance outlet, Dishwasher, water kettle, fridge w/o freezer, washing machine, hairdrier, computer, coffee machine, TV
5	Total outlets, total lights, kitchen TV, living room TV, fridge w/ freezer, electric oven, computer w/ scanner and printer, washing machine, hood
6	Plasma TV, lamp, toaster, hob, iron, computer w/ scanner and printer, LCD TV, washing machine, fridge w/ freezer
7	Hair dryer, washing machine, videogame console and radio, dryer, TV w/ decoder and computer in living room, kitchen TV, dishwasher, total outlets, total lights
8	Kitchen TV, dishwasher, living room TV, desktop computer w/ screen, washing machine, bedroom TV, total outlets, total lights



Example of power readings from GREEND



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Summary

- NILM is a resource-efficient way to detect appliance usage
- Can be used to give feedback on energy consumption and increase awareness
- Current smart meters do not provide information with sufficient measurement frequency
- Can be solved with dedicated meter
- Open challenges for computer scientists:
  - Present the aggregated data in an appealing way
  - Gamification strategies to motivate energy savings on the long run

References

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