When Privacy Meets Non-Intrusive Load Monitoring: Trade-off Analysis and Privacy Schemes via Residential Energy Storage

Sangyoung Park[1], Andrea Cominola[2], {sangyoung.park, andrea.cominola}@tu-berlin.de
[1]Smart Mobility Systems, Technical University of Berlin, Einstein Center Digital Future
[2]Smart Water Networks, Technical University of Berlin, Einstein Center Digital Future

Presenters

Dr. Sangyoung Park

- BS, EE, Seoul National University, South Korea, 2008
- PhD, EECS, Seoul National University, South Korea, 2014
- Postdoctoral researcher, Chair of Real-Time Computer Systems, Technical University of Munich, 2014-2018
- Junior Professor, Smart Mobility Systems, Technical University of Berlin & Einstein Center Digital Future, 2018-

Dr. Andrea Cominola

Photo credits: ECDF/PR/Felix Noak

- 10.2018 –: Assistant Professor, Smart Water Networks, Technical University of Berlin & Einstein Center Digital Future (Berlin, Germany).
- 2017: PhD Information Technology, Politecnico di Milano (Milan, Italy)
- 2013: double-degree MSc Environmental Engineering, Politecnico di Milano (Milan, Italy) and Politecnico di Torino (Turin, Italy)

Research Interests and Current Projects – Dr. Sangyoung Park

- Research Interests
  - Energy management of electric vehicles
  - Battery system design/management for electric vehicles
  - Enhancing safety of connected vehicles
  - Energy management of connected vehicle fleets
- Current/confirmed Projects
  - Ensuring Safety and Reliability of Vehicle Fleets using Vehicle-2-X Communication, (01.2019-)
  - Electrification of long-haul heavy-duty commercial vehicles with automated battery swapping station (10.2020-)
  - Urban critical infrastructure, International alliance for digital e-learning, e-mobility and e-research in academia, (10.2020-)

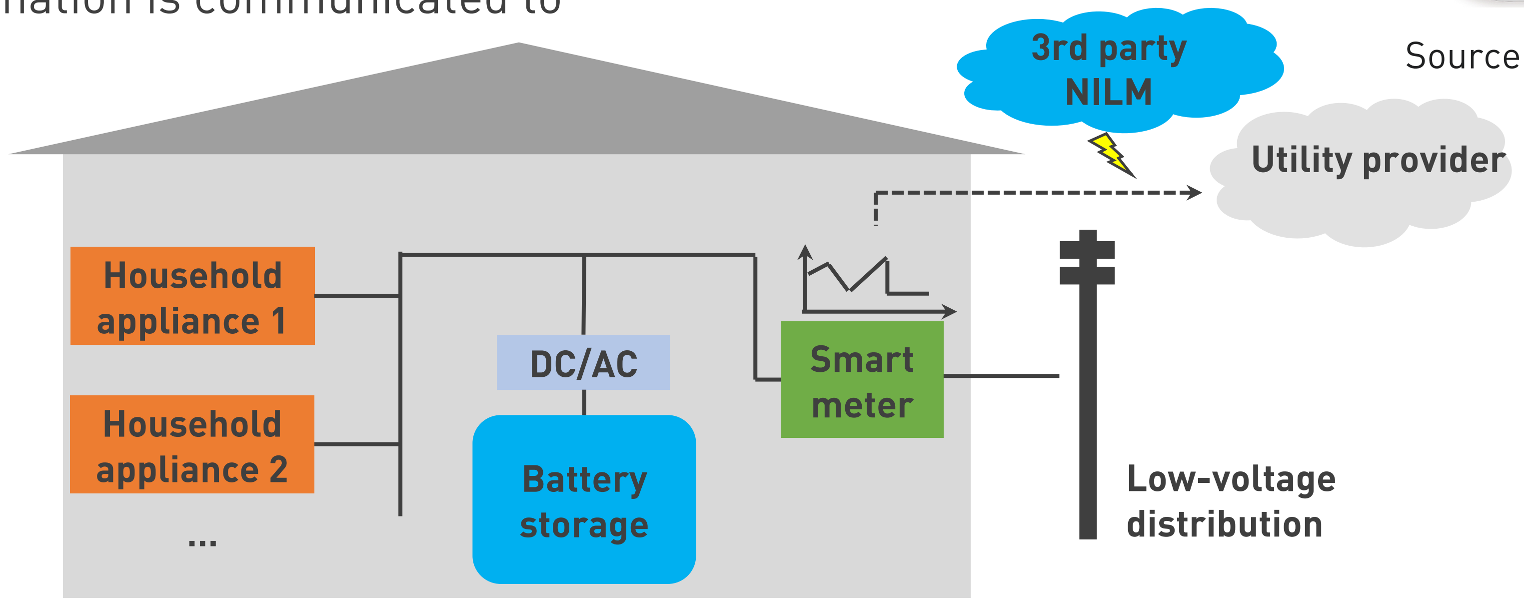
Research Interests and Current Projects – Dr. Andrea Cominola

- Research Interests
  - Digital water and energy metering
  - Water and energy demand modelling and management
  - Behavioral modelling
  - Water-energy nexus
- Selected current/confirmed Projects
  - 2020 - ongoing: *ide3a* - international alliance for digital e-learning, e-mobility and e-research in academia
  - 2020 - ongoing: Data Mining Dynamic Human Behaviors for Flood Risk Assessment in Coupled Human-environment Systems
  - 2019 – ongoing: Smart Water Survey (https://smartwatersurvey.com)

Smart Meters and Privacy

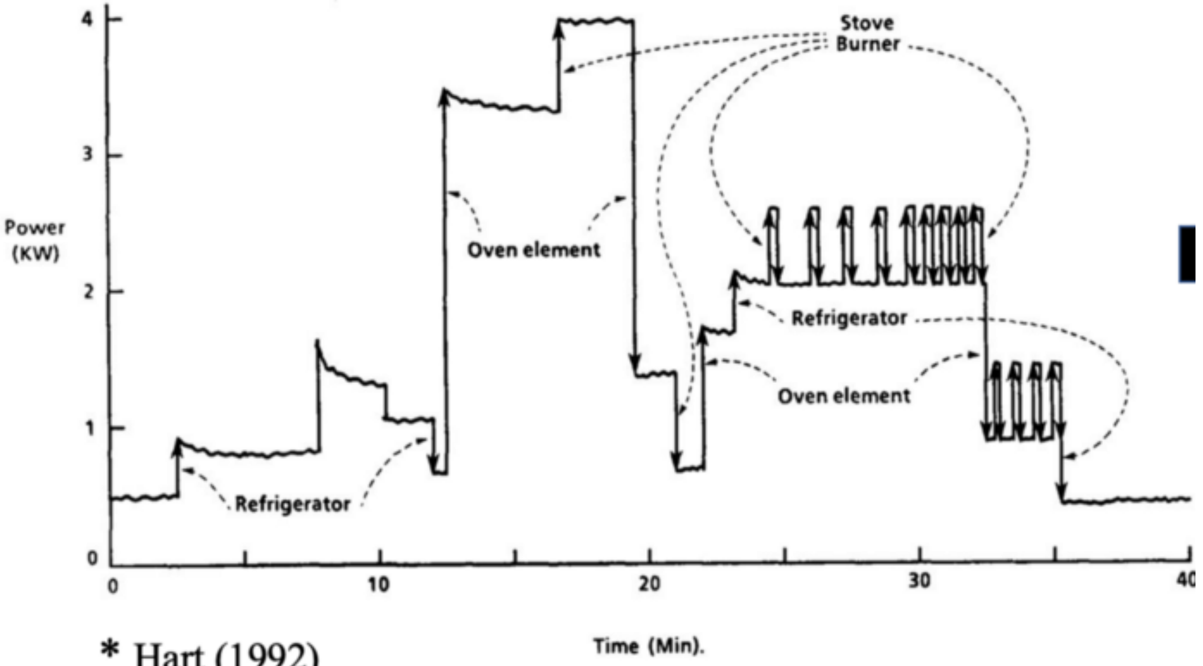
- Smart Meter
  - Records energy consumption, voltage/current and power factor
  - Communicate data to consumers & electricity suppliers
  - Provides clarity of the consumption behavior
  - Used for system monitoring and customer billing
- Privacy
  - Eletricity usage information is communicated to utility provider
  - Or possibly other 3rd parties

Source: EVB Energy Ltd



Non-Intrusive Load Monitoring (NILM) Algorithms

- Non-Intrusive Load Monitoring (NILM) algorithms
  - Estimating the electricity consumption of each appliance
  - Works with a meter measuring aggregated consumption: No need for sensors for each appliance
- Privacy concerns
  - Appliance usage profile may contain private information such as behavioral patterns
  - Routine times nobody is at home
  - Reveal times when occupants are taking a shower
  - Homeowners is not able to know whether a NILM algorithm is running remotely from the utility company or a third party

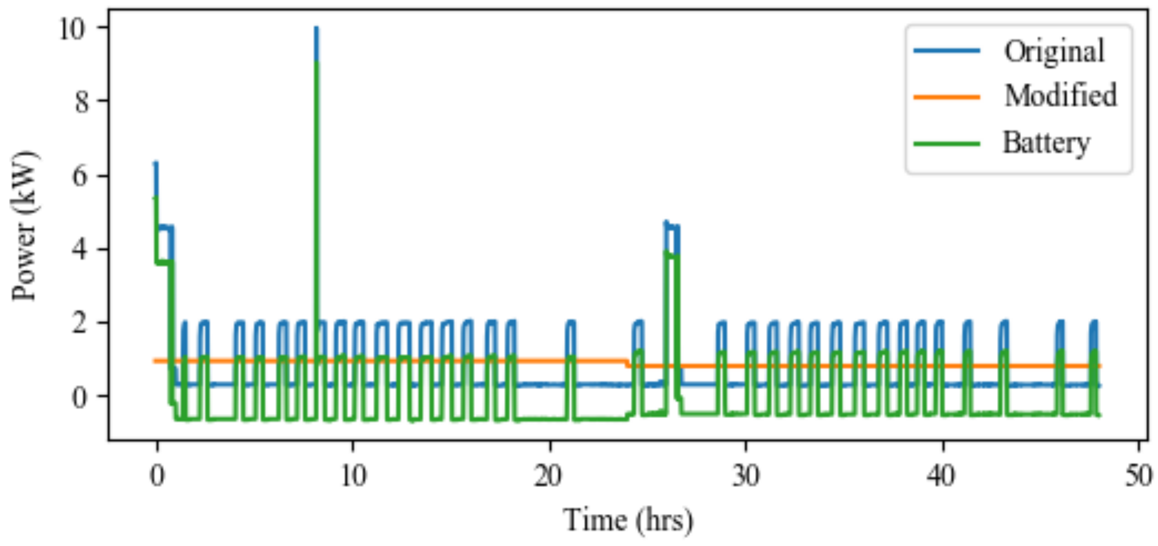


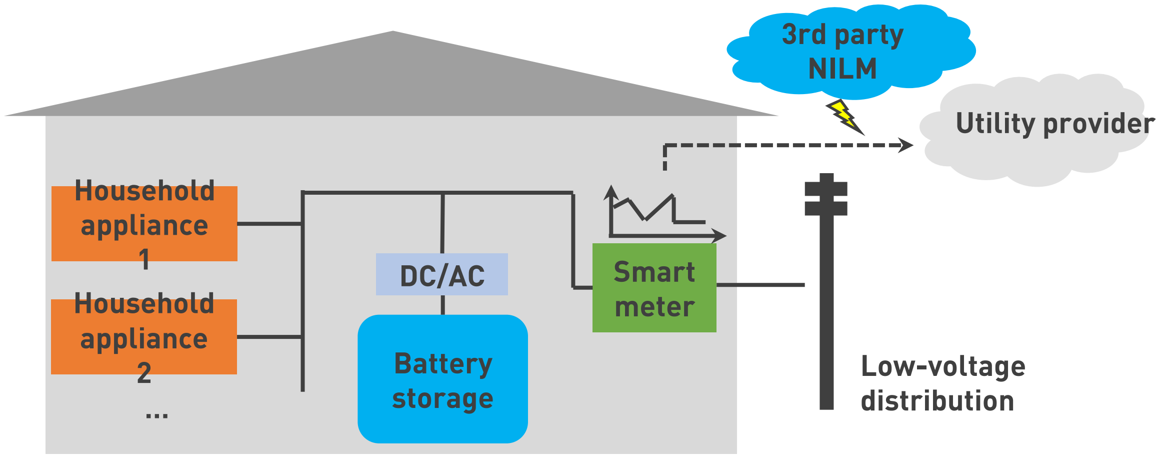
* Hart (1992)

G. W. Hart, "Nonintrusive appliance load monitoring," in *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870-1891, Dec. 1992, doi: 10.1109/5.192069.

Cost of Residential Privacy Protection using Battery Storage

- Residential battery systems can modify the consumption profile seen by the smart meter
- Completely flat profile results hides all patterns [Yang:TSG15, Kalogridis:11]
- However, the required battery capacity is prohibitive and costly [Proebstl:DATE19]
- Any privacy protection scheme using batteries should be **cost-effective**





Quantifying Privacy: What is Privacy?

- Mutual information [Proebstl:DATE19]
- RMS from the average power consumption
- Definitions from previous works are hard to connect with the general perceptions
- NILM algorithms provide the accuracy of appliance power consumption over every time step
- Finite-State (FS) F-score [Makonin:EE15]
  - $FS_i = \frac{2 \times PC_i \times RC_i}{PC_i + RC_i}$
  - Where RC_i and PC_i are recall and precision for an appliance, i, which take into account both accuracy and false positives
- Mean Absolute Percentage Error (MAPE)
  - $MAPE = \frac{1}{H} \sum_{t=1}^{H} \frac{|\hat{x}_t^i - x_t^i|}{K^i}$

Target NILM Algorithm: SparseNILM

- SparseNILM [Makonin:TSG16]

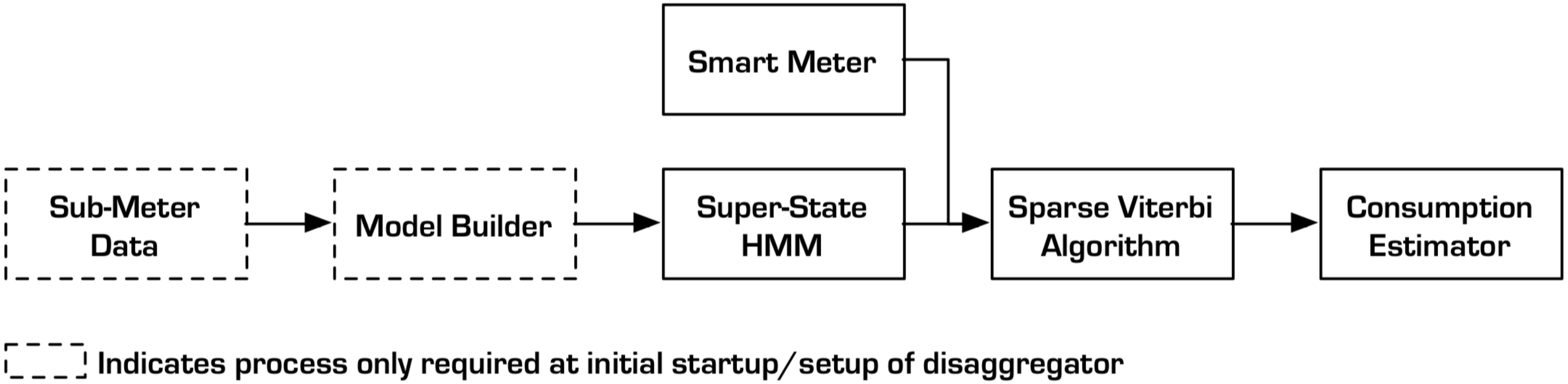


Figure source: Makonin, Stephen, et al. "Exploiting HMM sparsity to perform online real-time nonintrusive load monitoring." IEEE Transactions on smart grid 7.6 (2015): 2575-2585.

- SparseNILM code availability: *https://github.com/smakonin/SparseNILM* (Copyright (c) 2015 by Stephen Makonin)
- We aim at reducing the accuracy of the SparseNILM algorithm

Target NILM Algorithm: SparseNILM

- SparseNILM

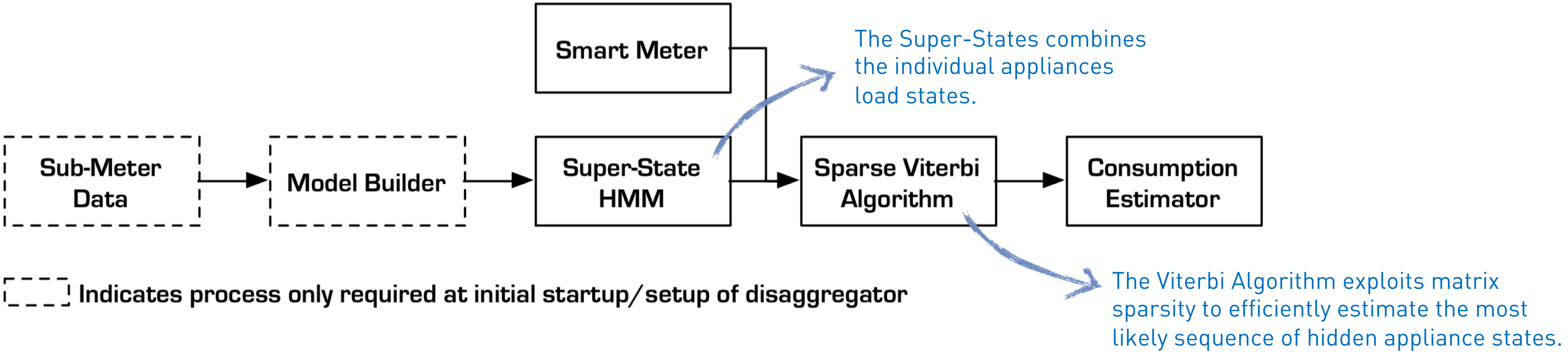
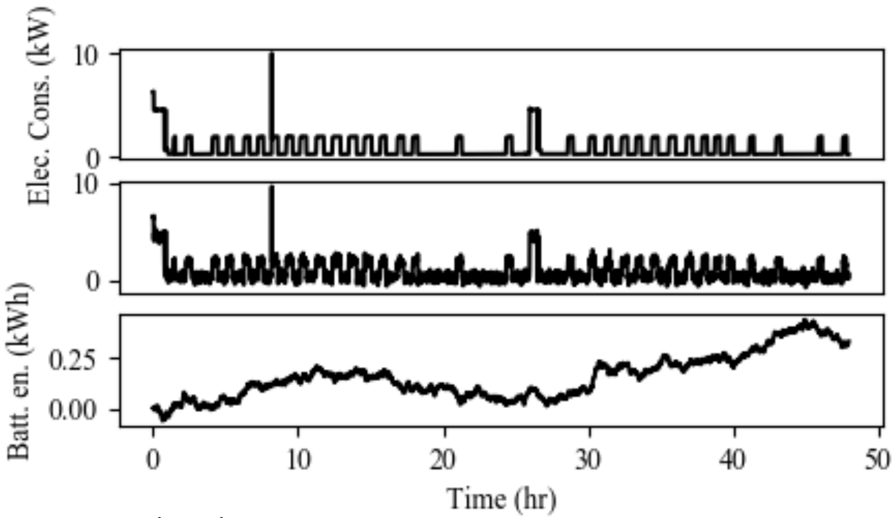


Figure source: Makonin, Stephen, et al. "Exploiting HMM sparsity to perform online real-time nonintrusive load monitoring." IEEE Transactions on smart grid 7.6 (2015): 2575-2585.

- SparseNILM code availability: *https://github.com/smakonin/SparseNILM* (Copyright (c) 2015 by Stephen Makonin)
- We aim at reducing the accuracy of the SparseNILM algorithm

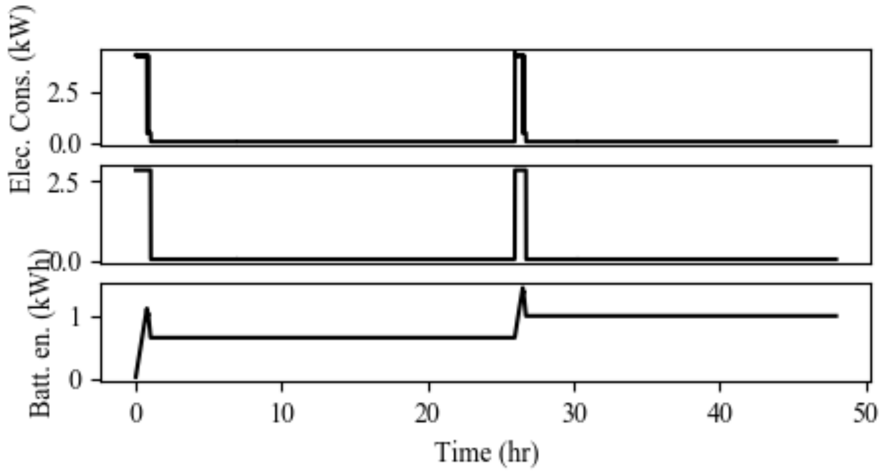
Methodologies

- M1: Add Gaussian noise to the whole duration of the profile
  - The simplest method to obfuscate the original profile
  - Does not require as much battery capacity as water-filling
- M2: Add Gaussian noise only when a particular appliance of interest is used
  - Check whether particular appliance can be hidden
  - Requires even less battery capacity than M1
- M3: Water-filling for a particular appliance of interest
  - Remove the shape of the profile and conserve only the average consumption



M1: (Up) Original profile of the whole house
(Middle) Gaussian noise with std of 0.3 kW,
(Low) Battery energy level to support M1

M3: (Up) Original profile of clothes dryer
(Middle) Water-filling for the dryer
(Low) Battery energy level to support M3

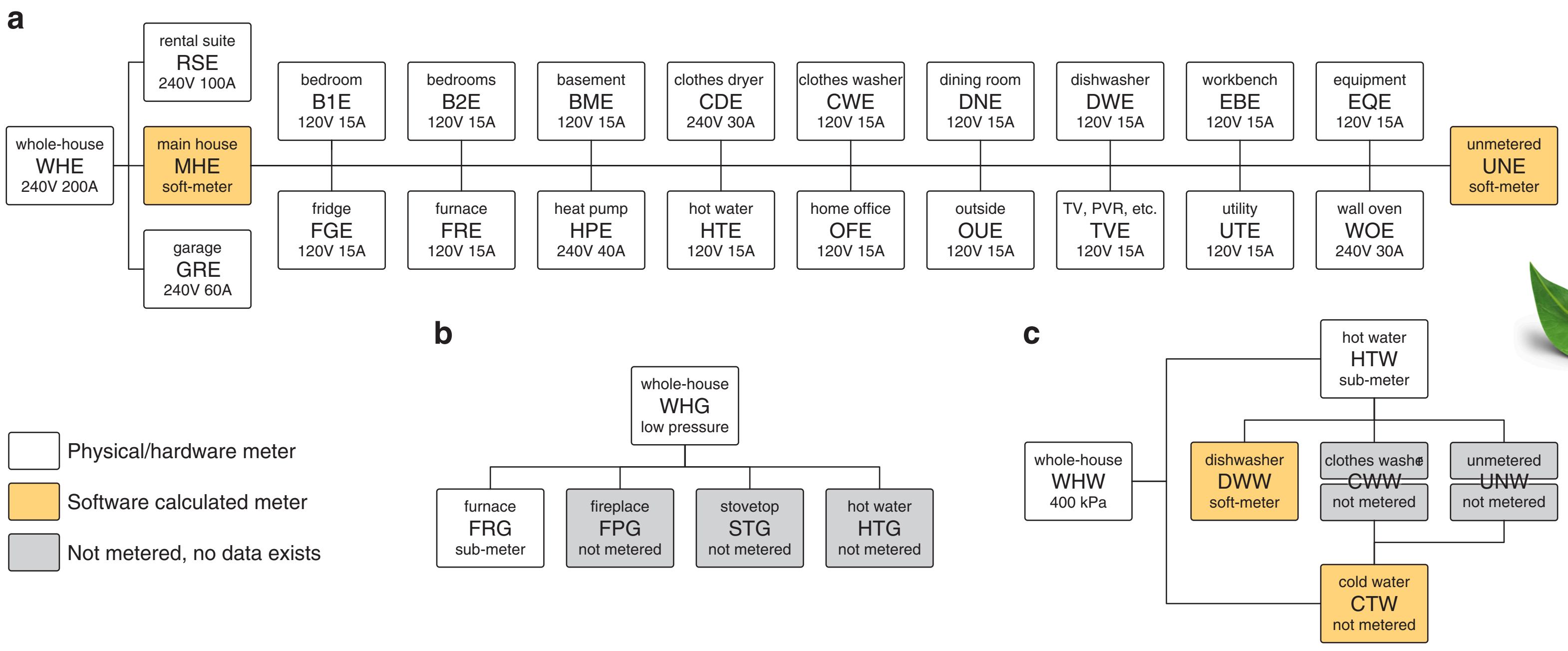


Methodologies

- M4: Spread-out the electricity consumption of particular application
  - M3 still preserves the average electricity consumption information while being used
  - Reduce the information by controlling the height of the rectangular profile in M3
- M5: Erase an appliance’s consumption
  - M4 still preserves the information about the time an appliance is being used
  - Remove this information by completely flattening out the profile
- M6: Day-wise water-filling for the whole electricity consumption profile
  - Conserves only the total average consumption

Dataset: AMPds Dataset [Makonin:EPEC13]

- The AMPds dataset helps researchers developing load disaggregation/NILM algorithms
- Electricity, water and natural gas measurements at one minute intervals
- Meters 24 loads at the electrical circuit breaker panel
- Total of 1,051,200 readings per meter for 2 years of monitoring

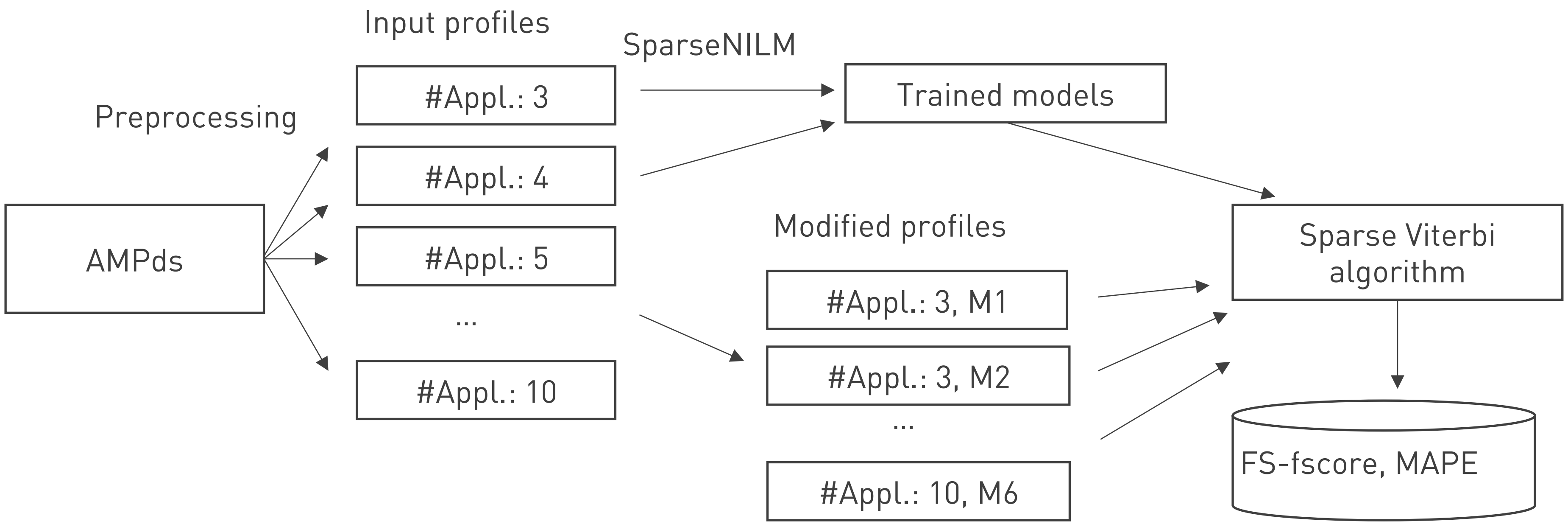


AMPds the Almanac of Minutely Power dataset

S. Makonin, et al., “Electricity, water, and natural gas consumption of a residential house in Canada from 2014 to 2014,” Scientific Data, vol. 3, no. 160037, pp.1-12, 2016.

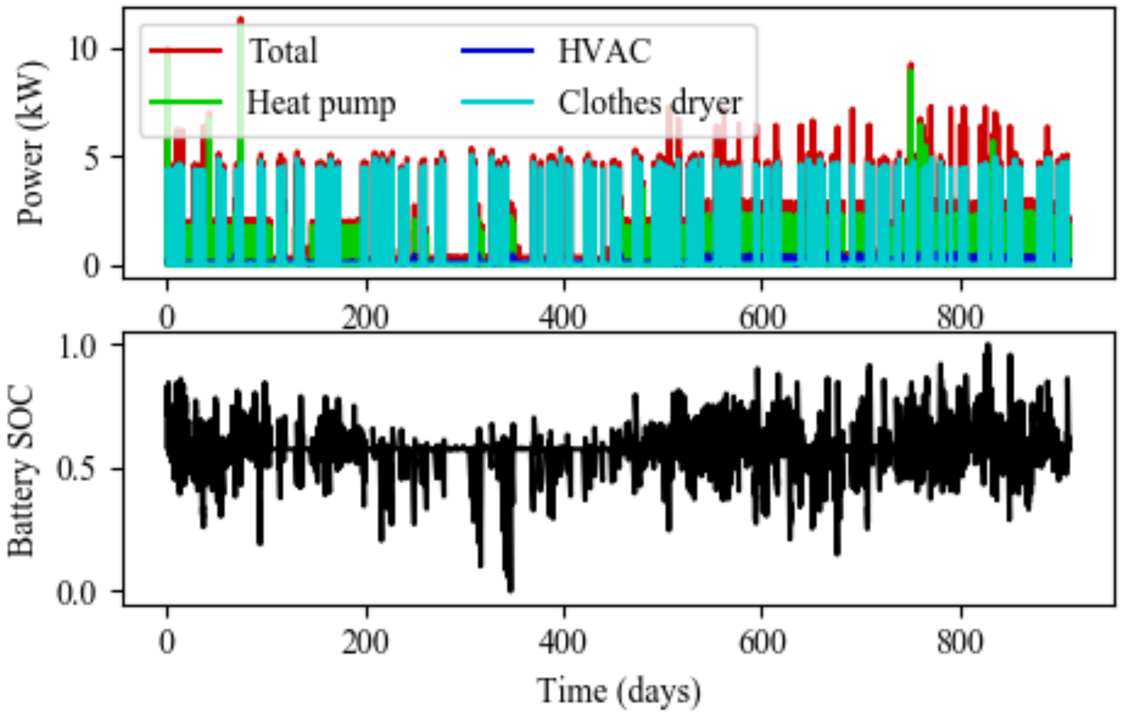
Evaluation Procedure

- Step 1: Pre-processing input profiles
  - Number of appliances have a huge impact on disaggregation performance
  - We select a subset of appliances to generate the whole consumption profile to analyze the performance
- Step 2: Train models using SparseNILM algorithm
- Step 3: Apply profile modification methods
- Step 4: Sparse Viterbi algorithm to generate evaluation scores



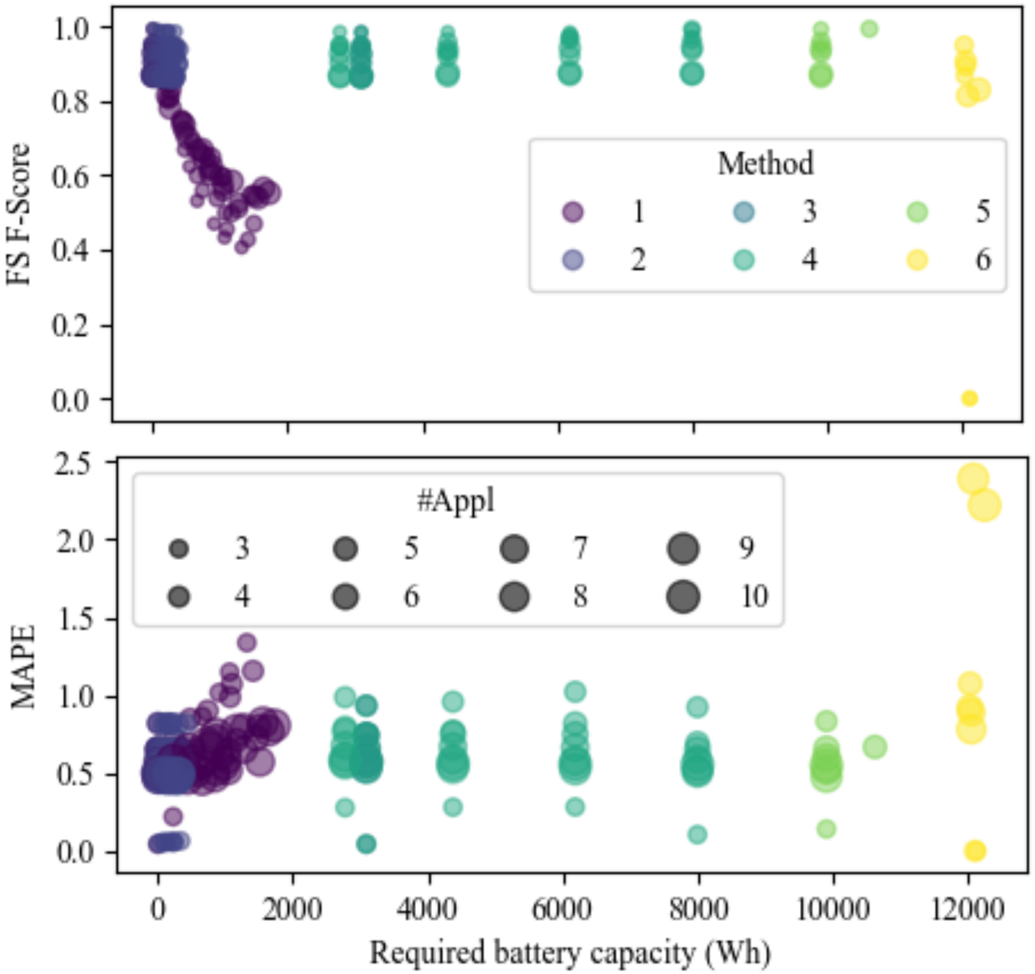
Results: Profile Modification

- Profile modification results
- M6: Day-wise water-filling requires 15.04 kWh battery capacity
  - The capacity is comparable to commercial products offered by Tesla or Enphase
  - But, still impractical becaues 100% of capacity is used for flattening the profile
  - Several thousands of dollars
- Battery State-Of-Charge (SOC) change over 2 years



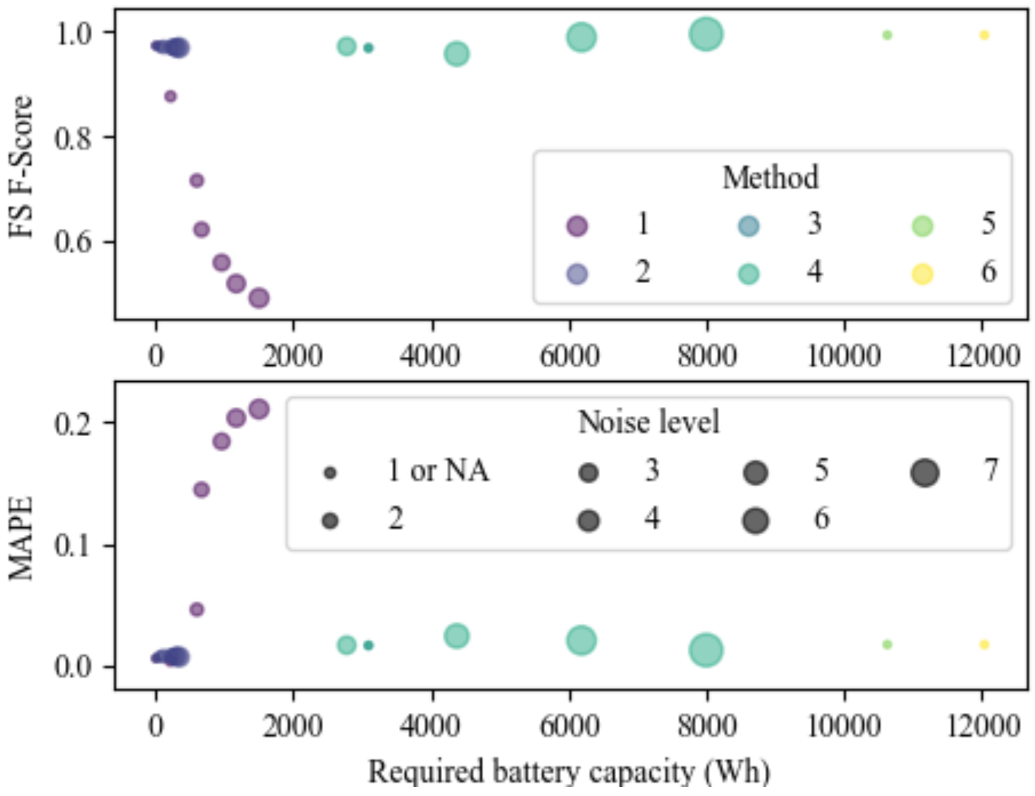
Results: FS F-Score & MAPE - All Appliances

- **Mean FS F-Score and Mean MAPE for all appliances**
- M1 & M2
  - Larger the noise, more battery capacity required
  - Accuracy degrades proportionally to the size of the noise
- M3 – M5
  - Battery required differs distinctly, but do not necessarily result in degraded FS F-Score
  - Falling accuracy is more related to # of appliances
- M6
  - Required battery size is the largest
  - Worse FS F-Score and MAPE occurs in this method
  - **Not so cost-effective compared to M1&M2**



Results: FS F-Score & MAPE – Clothes Dryer (CDE)

- **Mean FS F-Score and Mean MAPE for clothes dryer (CDE)**
- M1: Similar effects to all appliance results
  - Accurcay degrades proportionally to the size of the noise
- M2: Adding noise only when used does not harm accuracy
- M3 – M5: Battery required differs distinctly depending on the magnitude of modification , but do not necessarily result in degraded FS F-Score
- M6: Required battery size is the largest
  - Surprisingly, no impact on the estimation accuracy
  - Possibly due to the dominance of CDE profile over other signals



Conclusions & Future Work

- We investigated the effectiveness of a number of heuristic algorithms using **residential battery storage** in **preserving privacy** against a **NILM algorithm**
- Most prior works are based-on water-filling technique, which is effective in hiding the usage patterns, but very costly
- We assume that NILM algorithms will be used to extract privacy information and specifically aim at lowering its accuracy
- Our preliminar results indicate that **some intuitive methods do not necessarily yield significant drop** in NILM algorithm accuracy
- Future Work
  - **A systematic investigation for providing privacy protection against NILM algorithm is warranted**
  - Holistic cost analysis including the electricity bills should be performed

References

- **[Yang:TSG15]:** L. Yang, X. Chen, J. Zhang and H. V. Poor, "Cost-Effective and Privacy-Preserving Energy Management for Smart Meters," IEEE Transactions on Smart Grid, 2015
- **[Kalogridis:11]:** G. Kalogridis, Z. Fan and S. Basutkar, "Affordable Privacy for Home Smart Meters," IEEE International Symposium on Parallel and Distributed Processing with Applications Workshops, 2011
- **[Proebstl:DATE19]:** A. Pröbstl, S. Park, ,S. Steinhorst and S. Chakraborty, "Cost/Privacy Optimization in Smart Energy Grids," IEEE/ACM Design, Automation Test in Europe Conference Exhibition (DATE), 2019
- **[Makonin:TSG16]:** S. Makonin, F. Popowich, I. V. Bajić, B. Gill and L. Bartram, "Exploiting HMM Sparsity to Perform Online Real-Time Nonintrusive Load Monitoring," IEEE Transactions on Smart Grid, 2016
- **[Makonin:EE15]:** S. Makonin and F. Popowich, "Nonintrusive load monitoring {(NILM)} performance evaluation," Energy Efficiency, 2015
- **[Makonin:EPEC13]:** S. Makonin, F. Popowich, L. Bartram, B. Gill, I. V. Bajić, "AMPds: A public dataset for load disaggregation and eco-feedback research," IEEE Electrical Power & Energy Conference, 2013