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

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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**
  - Electrification of long-haul heavy-duty commercial vehicles with automated battery swapping station (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
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**
  - Electricity usage information is communicated to utility provider
  - Or possibly other 3rd parties

![Diagram of Smart Meter System](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

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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.
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)

\[ MAPE = \frac{1}{H} \sum_{t=1}^{H} \frac{|x^i_t - \hat{x}^i_t|}{K^i} \]
Target NILM Algorithm: SparseNILM

- SparseNILM [Makonin:TSG16]


- SparseNILM code availability: [https://github.com/smakonin/SparseNILM](https://github.com/smakonin/SparseNILM) (Copyright © 2015 by Stephen Makonin)
- We aim at reducing the accuracy of the SparseNILM algorithm
Target NILM Algorithm: SparseNILM

- SparseNILM

![Diagram of SparseNILM algorithm](image)

The Super-States combines the individual appliances load states.

The Viterbi Algorithm exploits matrix sparsity to efficiently estimate the most likely sequence of hidden appliance states.

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**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.

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- SparseNILM code availability: [https://github.com/smakonin/SparseNILM](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
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.

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 because 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
    - Accuracy 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 preliminary 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