Non Intrusive Load Monitoring: Systems, Metrics and Use Cases

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ABSTRACT

Buildings across the world contribute significantly to the overall energy consumption. Targeted feedback can help occupants optimise energy consumption. In our first work we present techniques for actionable feedback across fridges and air conditioning (HVAC) units, which can save upto 25% of fridge energy and identify homes needing feedback on HVAC setpoint schedule with 84% accuracy. In our next work, we do an extensive sensor deployment in a home in Delhi, India; monitoring appliance level power, home aggregate power and other ambient parameters. Our study presents various insights unseen in the developed world, such as: frequent voltage brownouts, poor network reliability, long lasting blackouts, heavy dominance of fridge and HVAC to overall energy consumption. Our study verifies that measuring appliance level power scales poorly in cost and maintenance. Non-intrusive load monitoring (NILM) is viewed as a viable alternative where machine learning techniques are used to break down aggregate household energy consumption into contributing appliances. Despite the existence of a rich volume of literature in NILM, it remained virtually impossible to compare NILM works due to: i) lack of existence of benchmarks; ii) previous work tested on single data set; iii) inconsistent metrics. To address these challenges we developed an open source toolkit: Non-intrusive load monitoring toolkit (NILMTK), designed specifically to enable the comparison of NILM algorithms. While many new NILM techniques have been proposed in recent times, it is not clear if these can enable energy saving and whether higher accuracy translates to higher energy saving. We explore these questions in our recent work and find that existing energy disaggregation techniques do not provide power traces with sufficient fidelity to support the feedback techniques we developed in our earlier work. Our results indicate a need to revisit the metrics by which disaggregation is evaluated.

1. RESEARCH SUMMARY

Buildings across the globe contribute significantly to the overall energy consumption [4]. Previous research has shown

the potential of energy saving by providing targeted energy consumption feedback to residents. We now discuss our work on providing actionable feedback based on appliance level power data.

1.1 Actionable feedback from appliance data

We focus on feedback on refrigerators and HVAC, because they contribute significantly to overall energy consumption and are available in most homes. In our first work [5], we develop a model that breaks the power trace of a refrigerator into three parts: baseline (when no one is using the fridge), defrost, and usage (energy consumption due to fridge usage). Then, we developed techniques to identify users with 1) much more energy due to fridge usage than the norm 2) much more energy due to defrost than the norm, or 3) fridges that are malfunctioning or misconfigured. We evaluated our model using a dataset with power traces from 95 refrigerators. We found that our model can break down fridge usage into its three components with only 4% error. Additionally, the three types of feedback could help users save up to 23%, 25% and 26% of their fridge energy usage, respectively. Similarly, we developed new techniques to differentiate homes with and without setback schedules on the HVAC system based on their HVAC power traces and outdoor weather patterns. This information can be used to give feedback to install a programmable thermostat. We evaluate these techniques with power traces from 58 homes and results indicate that our techniques can classify homes with 84% accuracy. Based on these results, we conclude that NILM does have the potential to provide targeted, actionable feedback that could lead to sustainable energy savings.

1.2 Residential deployment

Having found that appliance level power data can provide actionable feedback, we decided to do a dense residential deployment in a home in Delhi, India. All previous residential deployments had been done in the developed world. The philosophy behind our deployment [2] was to leave no stone unturned, whereby, we deployed 33 sensors for 73 days across a three storey home as shown in Figure 1. These sensors measured appliance level power consumption, aggregate home power consumption, utility water readings, and various ambient parameters such as temperature, light and motion. Our work highlighted the new challenges seen in the Indian settings, such as: frequent outages lasting up to 9 hours a day, voltage fluctuations upto 10 times more than that in the US, upto 25% internet packet drop in a day, heavy dominance of HVAC and fridges in overall energy (upto 50%). Our work also verified challenges in residential deployments discussed previously in the literature.
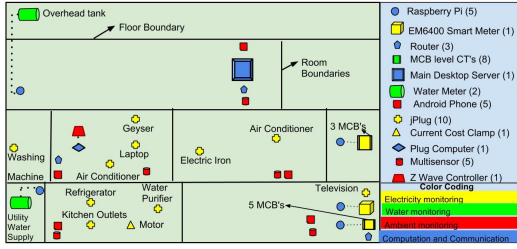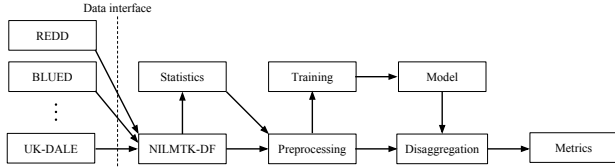
Figure 1: Home deployment schematic

Figure 2: NILMTK provides a complete pipeline from data sets to accuracy metrics

1.3 NILMTK

Challenges in dense residential deployments severely limit scaling up potential applications requiring appliance energy data. NILM is considered a viable alternative. However, despite more than 3 decades of research in NILM, it remained virtually impossible to empirically compare different algorithms, due to: i) different data sets used, ii) the lack of reference implementations of these algorithms, and iii) the variety of accuracy metrics employed. To address these challenges, we implemented the open source NILM toolkit (NILMTK), designed specifically to enable the comparison of NILM algorithms [3]. NILMTK provides a complete pipeline from data sets to accuracy metrics (Figure 2), lowering the entry barrier for researchers to implement a new algorithm. The initial version of NILMTK provided 2 benchmark NILM algorithms (combinatorial optimisation (CO) and factorial hidden Markov model (FHMM)) and data set parsers for 6 data sets. More recently, NILMTK underwent a major rewrite allowing out-of-core operations [6] and included the seminal NILM algorithm (Hart's) and additional data sets contributed by the data set authors. The success of any such endeavour is measured by the community uptake which is evidenced by recent works which use NILMTK [7, 1, 8, 5].

1.4 New metrics to evaluate NILM

While NILMTK now enables comparison of NILM algorithms across multiple data sets, two fundamental questions remain in NILM research: can these NILM techniques actually save energy and, if so, whether higher accuracy translates into higher energy savings. Having earlier established that appliance power traces can provide specific actionable feedback, we next evaluated the feedback produced by NILM algorithms. We applied benchmark NILM algorithms provided in NILMTK and found them to give results comparable to the state-of-art on traditional NILM metrics. However, Figure 3 and 4 show that on the metrics we care about, i.e. accuracy of feedback, NILM approaches fare poorly. These results indicate a need to revisit the metrics by which disaggregation is evaluated.

2. FUTURE WORK (CLOSING THE LOOP)

Our future work spans three directions: 1) evaluate use cases where disaggregation brings in a direct value by allowing
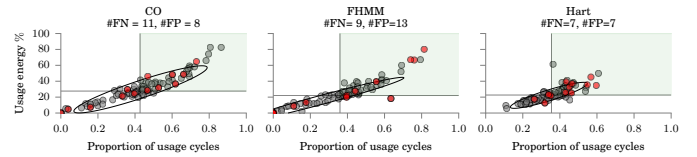

Figure 3: NILM algorithms show poor accuracy in identifying homes which need feedback for high fridge usage energy. Red dots indicate the homes which should be getting feedback based on analysis of submetered fridge data, while these algorithms would give feedback to all homes in the green region outside the elliptical boundary.
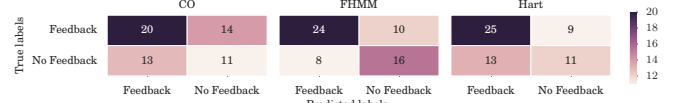

Figure 4: Classification of homes into those with setback schedules decreases from 84% with submetered power traces to 53%, 69%, and 62% respectively with power traces produced by the 3 NILM algorithms.

actionable feedback, e.g. energy apportionment; 2) improve the accuracy of existing NILM methods in context of the feedback methods we have already proposed ; and 3) evaluate these feedback methods in the wild through user studies, to understand the real world energy efficiency gains and sustenance of NILM based feedback.

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